UNIVERSITY OF SOUTHAMPTON

Essays on Financial Markets and the Macroeconomy

by

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UNIVERSITY OF SOUTHAMPTON <u>ABSTRACT</u>

SCHOOL OF ECONOMIC, SOCIAL AND POLITICAL SCIENCES DEPARTMENT OF ECONOMICS

Doctor of Philosophy

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This thesis investigates how disturbances on the demand side of credit markets affect economic fluctuations. In a first survey chapter, I analyse the importance of financial and non-financial shocks for economic fluctuations in macroeconomic models with financial frictions. With respect to existing similar surveys that analyse macro-financial linkages, my focus is to highlight the importance of exogenous shocks that originate on the demand side of finance for business cycle fluctuations, and show that the channels through which these shocks propagate to the economy are different from the financial accelerator mechanism which variants are at play in most macro-financial frameworks. Then, in a second chapter, I evaluate the relative effects of credit demand and supply shocks on economic fluctuations using UK data. To tackle the identification problem, I use the unique Bank of England's credit conditions survey data to construct loan supply and demand variables, which I then combine with macroeconomic variables to account for the linkages between the credit and the business cycles in a VAR setting where credit supply and demand shocks are identified using a combination of zero and sign restrictions, and estimate the model using Bayesian methods. I find that not only are credit demand shocks important for economic fluctuations, but also that they are as important as credit supply shocks for the UK economy, and this finding is robust across various alternative specifications. I also find that the UK economy, when subject to credit supply and demand shocks in a heterogeneous loan-types setting that includes business, mortgage and consumer loans, is significantly driven by the mortgage loans market. Finally, in a third chapter, to provide a structural interpretation for the main empirical finding and shed light on the transmission mechanisms of credit demand shocks to the real economy, I build a financial frictions DSGE model which simulations suggest that credit demand shocks propagate to the economy through both a Fisher deflation and a collateral channel. In addition, the model predicts that when borrowing constraints are allowed to bind occasionally, the effects of credit demand shocks are more persistent and amplified through the combined effects of the Fisher deflation and collateral channels on the economy.

Declaration of Authorship

I, Richard Kima, declare that this thesis entitled "Essays on Financial Markets and the Macroeconomy" and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

- 1. This work was done wholly while in candidature for a research degree at this University;
- 2. None of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution;
- 3. Where I have consulted the published work of others, this is always clearly attributed;
- 4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- 5. I have acknowledged all main sources of help;
- 6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- 7. None of this work has been published before submission.

Signed: Richard Kima

Date: 01 May 2019.

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Acronyms

BLS	Bank lending Survey
BoE	Bank of England
BVAR	Bayesian Vector Auto Regression
\mathbf{CCS}	Credit Conditions Survey
CSV	Costly State Verification
DSGE	Dynamic Stochastic General Equilibrium Model
ECB	European Central Bank
FEVD	Forecast Error Variance Decomposition
FRB	Federal Reserve Bank
GDP	Gross Domestic Product
IRF	Impulse Response Function
LTV	Loan to Value
ONS	Office for National Statistics
SLOOS	Senior Loan Officer Opinion Survey
SVAR	Structural Vector Auto Regression
TFP	Total Factor Productivity
VAR	Vector Auto Regression

To My Mum.

Chapter 1

General Introduction

The interactions between financial factors and the real economy have been studied over the past three decades, and more extensively since the last financial crisis. Central in these works is the role played by financial frictions in propagating and amplifying financial and non-financial shocks. These frictions which inclusion in dynamic macroeconomic frameworks can be traced back to Bernanke and Gertler (1989), are now widely accepted as important drivers of business cycle fluctuations.

Financial frictions often arise from credit markets imperfections in the form of asymmetric information and enforcement issues that give rise to agency problems. With regard to information asymmetries, because ex-ante borrowers know more than lenders about their projects' riskiness or expected returns and whether they will exert sufficient effort, adverse selection and moral hazard problems may arise. For example, if the debt repayment depends on the project's performance which in turn depends on unobservable effort, the borrower may have an incentive to choose low effort since the lender is unable to observe its actions. As for the enforcement issues, lenders may encounter difficulties in enforcing contracts ex-post because of legal and institutional constraints which do not allow for efficient settlements. For example, there could be legal limits to what the lender can enforce. Both agency problems lead to incomplete credit markets as lenders may refrain from lending in the first place if contracts are not incentive-compatible or fully enforceable.¹

Information asymmetries and limited enforcement of contracts have been accommodated in the literature in two main ways. First, the use of Townsend (1979)'s costly state verification (CSV thereafter) scheme to deal with the asymmetric information problem, as initiated by Bernanke

¹Other forms markets incompleteness used in the literature include the restriction for agents to only hold bonds and non state-contingent assets (e.g., when they cannot issue equity), and the imposition of an exogenous limit to the total amount of debt that they can have access to. An example of this credit quantity rationing is Stiglitz and Weiss (1981) where lenders face a lemons problem as in Akerlof (1970).

et al. (1999). The CSV implies that a debt contract between a borrower and a lender is the best way to overcome asymmetric information between the two parties.² Second, the requirement of collaterals used by Kiyotaki and Moore (1997), in order to mitigate the limited enforcement of contracts.³ These later borrowing constraints which limit the amount of debt financing by the value of the underlying collateral, have been extended in the post-crisis literature by the possibility of constraints to equity financing. These constraints limit the extent to which borrowing firms can sell risky claims depending on their stake in a given project; this "skin in the game" condition, boils down to an incentive-compatibility constraint.

Most works on macro-financial linkages that incorporate financial frictions, have extensively analysed how disruptions in credit supply affect the business cycle. Instead, this thesis is concerned with how and to what extent disturbances on the demand side of credit markets affect economic fluctuations. These credit demand disturbances broadly include all shocks that directly affect the borrowing behaviour of households and firms, and hence their consumption and investment choices. These shocks that affect borrowers' choices can be associated with events such as a decreased or increased confidence in future expected income streams or investment opportunities, and more generally to optimism or pessimism about the future economic outlook. Loan demand disturbances can also be linked to shocks that affect agents' borrowing capacity through shifts in their loan-to-value ratios. Finally, credit demand may also stem from a voluntary deleveraging process due for instance to a downward adjustment of mortgages rates as witnessed in the US following the accommodating monetary policy by the Federal Reserve in the aftermath of the Great Recession.

I start in the first chapter with a review of the literature on the interaction between financial factors and the macroeconomy, focusing on both the effects and transmission channels of supplyand demand-side financial shocks, as well as non-financial shocks, for the economy. Then, in the second chapter, using UK data, I evaluate the relative importance of credit demand versus credit supply shocks for economic fluctuations in a Bayesian VAR framework. Finally, the third chapter analyses the channels through which loan demand shocks propagate to the economy in a DSGE setting.

The survey chapter analyses the importance of financial and non-financial shocks for economic fluctuations in macroeconomic models with financial frictions. I first review how financial frictions frameworks subject to non-financial shocks lead to business cycle fluctuations through the so-called

²Debt is the optimal contract since it minimizes the socially wasteful monitoring costs. As long as the debt is repaid in full, there is no need to verify the true state which is only verified in the case of default.

 $^{^{3}}$ An earlier paper featuring collaterals but in the form of endogenous debt constraints in a complete markets setting is Kehoe and Levine (1993).

financial accelerator mechanism. Then I highlight how the post-2008 financial crisis models that directly incorporate financial shocks in settings with financial intermediaries, generate higher economic fluctuations compared with the pre-crisis first generation financial frictions models.

For the post-crisis literature in particular, I distinguish between financial shocks that originate from the supply side of credit and those originating from the demand side. Models with supplyside shocks constitute the great bulk of this literature. They include settings with financial shocks triggered by sharp changes in banks' balance-sheets, settings with shocks directly affecting banks' lending behaviour (e.g., risk appetite, competition pressure), and more recent frameworks with shocks that primarily stem from sharp variations in banks' liquidity either through bank runs, the inter-bank market, or shadow banking. However, less analysed demand-side financial shocks settings are characterised by exogenous disturbances that induce borrowers to voluntarily lever-up or de-lever, resulting in amplification effects on the economy through a Fisher debt-deflation channel.

With respect to the existing surveys that also analyse macro-financial linkages, my focus is to highlight the importance of exogenous shocks that originate on the demand side of finance for business cycle fluctuations. I then show that the channels through which these shocks propagate to the economy are different from the financial accelerator mechanism which variants are at play in most macro-financial frameworks. Whereas the supply-side literature extensively grew since the crisis, more investigations need to be carried out to further analyse both the effects for economic activity and the policy implications of demand-side financial shocks.

In an attempt to address the scant investigation of demand-side financial shocks, the second chapter of the thesis analyses the relative effects of credit demand and supply shocks on economic fluctuations using UK data. In particular, the Bank of England's credit conditions survey data are used to construct loan supply and demand variables, which are then combined with standard macroeconomic variables to account for the linkages between the credit and the business cycles. This analysis is carried out in a structural vector auto-regression (SVAR) setting where credit supply and demand shocks are identified using a combination of zero and sign restrictions. Estimation and inferences are then conducted using Bayesian methods.

The model estimation reveals that an exogenous negative loan demand shock leads to a contraction in economic activity comparable to the one resulting from a similar credit supply shock. This result is at odds with the common belief that credit demand shocks are not relevant for the business cycle and therefore should not retain policy makers' attention. The finding is robust to several alternative specifications, including the inclusion of additional control variables,

the use of alternative definitions and proxies for the credit variables, the estimation of the model with flat priors, the use of alternative identifying assumptions, and the assignment of arbitrary weights to the different types of loans. Another interesting result is that the UK economy, when subject to credit supply and demand shocks in a heterogeneous loan-types setting that includes business, mortgage and consumer loans, is significantly driven by the mortgage loans market.

Finally, in the third chapter of the thesis, to provide a structural interpretation for the previous empirical result that credit demand shocks are important for economic activity and shed light on the transmission mechanisms of these shocks to the real economy, I build a financial frictions DSGE model featuring borrowing households and firms as well as a banking sector. The model simulations suggest that credit demand shocks propagate to the economy through both a Fisher deflation and a collateral channel. In addition, the model predicts that when borrowing constraints are allowed to bind occasionally, the effects of credit demand shocks are more persistent and amplified through the combined effects of the Fisher deflation and collateral channels on the economy.

Chapter 2

Financial Factors and the Macroeconomy: a Survey

This survey analyses the importance of financial and non-financial shocks for economic fluctuations in macroeconomic models with financial frictions. I first review how financial frictions frameworks subject to non-financial shocks lead to business cycle fluctuations through the financial accelerator mechanism. Then I highlight how the post-2008 financial crisis models that directly incorporate financial shocks in settings with financial intermediaries, generate higher economic fluctuations compared with the first generation of financial frictions models of the pre-crisis period. In this post-crisis literature, I distinguish between financial shocks that originate from the supply side of credit and those originating from the demand side. With respect to existing similar surveys that analyse macro-financial linkages, my focus is to highlight the importance of exogenous shocks that originate on the demand side of finance for business cycle fluctuations, and show that the channels through which these shocks propagate to the economy are different from the financial accelerator mechanism which variants are at play in most macro-financial frameworks.¹

 $^{^1{\}rm I}$ am grateful to Michael Hatcher, Jose Olmo, Alessandro Mennuni, and Chiara Forlati for comments and feedbacks on this paper.

2.1 Introduction

Given the large number of works that study the interactions between financial factors and the real economy and existing surveys with various specific focus, my objective in this survey is to provide a synthesis of the existing literature that comprehensively analyses the working mechanisms of these financial and real economy inter-linkages in dynamic macroeconomic settings, depending on the nature of the shocks that affect the economy. With respect to existing similar surveys, my focus is to highlight the importance of exogenous shocks that originate on the demand side of finance for business cycle fluctuations, and show that the channels through which these credit demand shocks propagate to the economy are different from the financial accelerator mechanism which variants are at play in most of the macro-financial frameworks in the literature. For that, I organise the survey in three main parts.

The first part is devoted to the analysis of financial frictions models subject to non-financial shocks. These frameworks constitute the great bulk of the pre-crisis literature. Pioneered by Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999), these models show how the effects of monetary policy and TFP shocks on the economy are more amplified in dynamic macroeconomic settings where financial frictions are taken into account, compared to standard frameworks without financial frictions. The propagation mechanism of these non-financial shocks works as follows. An initial adverse shock (e.g., restrictive monetary policy shock, negative TFP or preference shock) that leads to a decrease in asset prices and net worth will contract borrowers' access to external financing, resulting in lower investment and consumption, and decreased production alike. In turn, these changes are amplified because of the presence of financial frictions, and are persistent as asset prices and economic activity fluctuate, which depresses further net worth and results in lower demand and availability of external financing. This vicious cycle effects propagate over time, with adverse feedbacks between the financial factors and the real economy.

The second part of the survey covers models with financial shocks that generally occur directly in the financial sector in frameworks which explicitly incorporate financial intermediaries. This second group of models which has witnessed a tremendous development since the last crisis, mostly focuses on shocks originating from the supply side of credit - through banks and other financial intermediaries expanding or restricting access to credit for various reasons including their balance-sheets' strength, their risk appetite, regulatory capital requirements, or borrowers' riskiness, among others, - and shows how these shocks propagate to the real economy through turn lowers consumption and investment expenditures as less credit is extended to borrowing households and firms. As a result of these lower spendings, asset prices fall, decreasing collaterals' value through a first channel, which along with the financial frictions, reduces further loan supply but also loan demand through expectations of future lower asset prices. Together, these adverse loan supply and demand effects depress further economic activity. On top of this, there is a second channel through which the falling asset prices leads to higher credit losses and lower profits for financial intermediaries, which erodes further their balance-sheets, resulting in even less credit extended to borrowers and exacerbating further the effects on the real economy.

Finally, the third part of the survey addresses the growing debt (de-)leveraging literature where financial shocks rather arise from the demand side of credit in the form of exogenous disturbances that push borrowers to lever-up or de-lever. These exogenous loan demand shocks also lead to economic fluctuations, yet through a channel different from the financial accelerator propagation mechanism in play in the two previous transmission channels above and where changes in credit demand only occur endogenously. Typically, an exogenous loan demand shock that pushes borrowers to de-lever, results in a reduction in consumption and investment, thus contracting aggregate demand and the general level of prices and increasing the real burden of debt through the so-called Fisher deflation channel. The higher real cost of debt (due to lower price levels) leads to even more contraction in loan demand along with lower interest rates (through markets adjustment mechanisms) in subsequent periods, putting further downward pressure on aggregate demand and prices which can be exacerbated when the zero lower bound on the nominal policy rate is reached.

Existing surveys that also analyse the macro-financial linkages, yet with different focus, include Claessens and Kose (2017), Duncan and Nolan (2018), Brunnermeier et al. (2012), and Quadrini (2011) among others.

In particular, Claessens and Kose (2017) surveys the literature that analyses the inter-relations between macroeconomic and financial factors by considering two channels: The first channel analyses how changes in borrowers' balance sheets can amplify macroeconomic fluctuations, whereas the second channel highlights the importance of lenders' balance sheets and liquidity provision for the real economy. Yet, unlike Claessens and Kose (2017) which also surveys the literature on the interactions between asset prices and the macro-economy in addition to the macro-financial linkages, my aim is mostly to highlight how the macro-finance inter-linkages unfold from the demand side of the credit market.

Another recent survey by Duncan and Nolan (2018) focuses on the way financial intermediaries have been incorporated in DSGE models, in the recent post-crisis research. They summarize the key modelling developments around credit intermediation since the crisis, that have been key in fostering our understanding of the role played by the financial sector in the propagation of shocks and the consequences of financial instability for the macro-economy. My survey complements theirs by highlighting the role of the supply side of credit in the transmission of shocks to the economy.

Brunnermeier et al. (2012)'s focus is on the macroeconomic implications of financial frictions. In particular, they emphasize how different forms of liquidity constraints have led to asymmetric and highly non-linear effects. Finally, Quadrini (2011) points out at how accounting for working capital in models with financial frictions and allowing for financial shocks may lead to higher amplification effects, compared with the standard pre-crisis financial frictions models. Yet, it is unclear whether the financial shocks highlighted in his survey are supply or demand side phenomena, and financial intermediaries are still a veil as in most of the pre-crisis frameworks.

Because the focus of this survey is on the analysis of the interactions between financial factors and the macro-economy in dynamic models, I do not cover the empirical literature that uses long series data on financial crises to report a number of salient facts and features of business and financial cycles from an historical perspective, documenting how periods of steady and strong credit growth played an important role in shaping recessions and recoveries.² Nor do I consider the numerous studies that analyse the empirical relevance of financial factors in microeconomic settings using firm or household level data (an exception however is section 2.4.2.2 on micro-econometric settings highlighting debt deleveraging), or reduced-form VAR and other time series models using macroeconomic variables (such studies include Bernanke and Gertler (1995), Lown and Morgan (2006), Gilchrist and Zakrajšek (2012), and Bassett et al. (2014) among many others).³

This survey is organized as follows. Section 2.2 analyses key financial frictions models subject to non-financial shocks, whereas section 2.3 reviews supply-side financial shocks. In section 2.4, I first propose a simple two-period model to help shed light on how credit demand-side

 $^{^{2}}$ For an historical analysis of financial crises, including banking, currency or sovereign debt crises, the reader can refer to Duncan and Nolan (2018) and references therein.

 $^{^{3}}$ For empirical evidence focusing on corporate investment and household consumption, the reader can refer to Claessens and Kose (2017) and references therein

shocks propagate to the real economy, before surveying the growing literature that studies debt (de-)leveraging in both macroeconomic and microeconomic settings. Finally, section 2.5 concludes and proposes directions for further research.

2.2 Models with Non-Financial Shocks

Macroeconomic models incorporating financial frictions and subject to non-financial shocks have mostly been developed during the pre-crisis period. Most of them focus on balance-sheet constraints facing non-financial firms.

2.2.1 The Core Models

The workhorse models which most of the literature builds upon are Bernanke et al. (1999) and Kiyotaki and Moore (1997). Even though these two core frameworks are different in a number of technical details, they share some common features. In particular, both analyse how financial frictions amplify the effects of exogenous shocks to the economy. In addition, aggregate shocks (e.g. TFP shocks) play an important role in these models as agents cannot insure against them. Hence, an adverse uninsurable aggregate shock leads to agents fire-selling their assets, which exacerbates the effects of this negative shock in subsequent periods. This section exposes in more details how non-financial shocks, namely TFP and monetary policy shocks, are propagated to the economy in these two core models.

2.2.1.1 Bernanke, Gertler, and Gilchrist (1999)

Bernanke et al. (1999) (BGG99 henceforth) introduce Townsend (1979)'s costly state verification (CSV) scheme into a dynamic New Keynesian model to show how financial frictions can help to significantly propagate and amplify the effects of both real and nominal shocks to the economy. In particular, they find that the effects on economic activity of a 25 basis point increase in the monetary policy rate are almost doubled by the financial accelerator mechanism; the impact response of output to such restrictive monetary policy is almost about 50% greater thanks to the financial frictions.

BGG99's Framework in more details

BGG99 assume a continuum of infinitely lived households of unity mass that consume and save at the risk-free interest rate, and borrowing entrepreneurs with finite life horizon characterized by a constant survival probability γ , implying an expected lifetime of $\frac{1}{1-\gamma}$. This finite life assumption aims both to capture the ongoing births and deaths of firms, and prevent entrepreneurs from accumulating enough wealth so that they may be able to entirely self-finance their investment.

At time t, entrepreneur j purchases, for use at time t + 1, capital K_{t+1}^j at price Q_t . At the beginning of period t + 1, he has available net worth N_{t+1}^j , and needs to borrow the difference B_{t+1}^j between his expenditures on capital goods and his net worth

$$B_{t+1}^j = Q_t K_{t+1}^j - N_{t+1}^j$$

The entrepreneur's realized return on capital is given by $w^j R_{t+1}^k$, where w^j is its idiosyncratic shock, iid across entrepreneurs, and R_{t+1}^k is the ex-post aggregate optimal return to capital, common to all the entrepreneurs. Following the CSV assumption, the monitoring costs are set equal to a fraction $\mu \in (0, 1)$ of the realized gross pay-off to the entrepreneur's capital, that is $\mu w^j R_{t+1}^k Q_t K_{t+1}^j$.

Taking the ex-ante values of $Q_t K_{t+1}^j$ and B_{t+1}^j and the ex-post value of R_{t+1}^k as given, BGG99 characterize the partial equilibrium optimal borrower-lender contract by a gross non-default loan rate Z_{t+1}^j and a threshold value of the idiosyncratic shock w^j denoted \bar{w}^j , such that for values of the shock greater than or equal to \bar{w}^j , the firm is able to repay the loan at the contractual rate Z_{t+1}^j , that is

$$\bar{w}^j R_{t+1}^k Q_t K_{t+1}^j = Z_{t+1}^j B_{t+1}^j.$$

Optimal \bar{w}^{j} and Z_{t+1}^{j} are determined by the requirement that the lender receives an expected return equal to the opportunity cost of its funds, that is the gross risk-free rate R_{t+1} . Therefore, the optimal loan contract satisfies:

$$\left[1 - F(\bar{w}^j)\right]\bar{w}^j + (1 - \mu)\int_0^{\bar{w}^j} w dF(w) R_{t+1}^k Q_t K_{t+1}^j = R_{t+1}(Q_t K_{t+1}^j - N_{t+1}^j).$$
(2.1)

where $F(w^j)$ is w^j 's cumulative distribution function.

Given the loan contract, the firm's expected gross return is derived as:

$$E\left\{\left[1-\mu\int_{0}^{\bar{w}^{j}}wdF(w)\right]\frac{R_{t+1}^{k}}{E\left\{R_{t+1}^{k}\right\}}\right\}E\left\{R_{t+1}^{k}\right\}Q_{t}K_{t+1}^{j}-R_{t+1}(Q_{t}K_{t+1}^{j}-N_{t+1}^{j})$$
(2.2)

In this partial equilibrium setting, the investment and contracting problem thus reduce to choosing K_{t+1}^j and a schedule for \bar{w}^j as a function of the realized values of R_{t+1}^k , in order to maximize Equation (2.2) subject to Equation (2.1). The distribution of the idiosyncratic shock w^j , the price of capital Q_t , and the amount of net worth N_{t+1}^j , are all taken as given in the maximization problem. The necessary first order conditions yield the following expression for the optimal demand for capital:

$$Q_t K_{t+1}^j = \frac{E[R_{t+1}^k]}{R_{t+1}} N_{t+1}^j$$
(2.3)

Hence, Equation (2.3) which also defines the entrepreneur's optimal leverage $\frac{Q_t K_{t+1}^j}{N_{t+1}^j}$, shows that in equilibrium, each entrepreneur's spending on capital is proportional to its net worth, with the proportionality coefficient determined by the expected discounted return on capital $\frac{E[R_{t+1}^k]}{R_{t+1}}$. Besides, Equation (2.3) re-expressed as

$$\frac{E[R_{t+1}^k]}{R_{t+1}} = \frac{Q_t K_{t+1}^j}{N_{t+1}^j}$$
(2.4)

shows the inverse relationship between the external finance premium defined as the expected discounted return on capital, and the entrepreneur's net worth. Intuitively, higher levels of net worth are associated with increased self-financing, which reduces the external finance dependency. The related borrower-lender agency problem is therefore lower, resulting in a smaller external finance premium paid by the borrower in equilibrium.

BGG99 then embed the partial equilibrium contracting problem in a dynamic general equilibrium model in which they endogenise all the variables that were taken as given in the partial equilibrium. Since all entrepreneurs face the same aggregate return on capital R_{t+1}^k , they therefore face the same premium on external funds so that summing across firms implies that the following equation for market demand of capital holds in the aggregate:

$$E\{R_{t+1}^k\} = \frac{N_{t+1}}{Q_t K_{t+1}} R_{t+1}$$
(2.5)

with K being the aggregate demand for capital, and N the aggregate stock of entrepreneurs' net worth.

If V_t denotes entrepreneurs' aggregate equity, then their aggregate net worth can be expressed as:

$$N_{t+1} = \gamma \left[R_t^k Q_{t-1} K_t - \left(R_t + \frac{\mu \int_0^{\bar{w}^j} w R_t^k Q_{t-1} K_t dF(w)}{Q_{t-1} K_t - N_{t-1}} \right) (Q_{t-1} K_t - N_{t-1}) \right]$$
(2.6)

where $\frac{\mu \int_{0}^{\bar{w}^{j}} w R_{t}^{k} Q_{t-1} K_{t} dF(w)}{Q_{t-1} K_{t} - N_{t-1}}$ is the ratio of default costs to quantity borrowed. Equations (2.5) and (2.6) are the two main equations of BGG99's model. While (2.5) characterizes the endogenous variation in net worth, (2.6) describes how movements in net worth influence the cost of capital.

2.2.1.2 Kiyotaki and Moore (1997)

Kiyotaki and Moore (1997) (KM97 henceforth) propose a theoretical framework in which endogenous fluctuations in the market price of an asset (land in their case) are the main sources of changes in borrowers' net worth, and hence in investment and production. In their model, land is used as collateral for loans, and also as capital for output good production. They show that by allowing for endogenous fluctuations in land price, an adverse productivity shock that leads to a decrease in this price, gets amplified as such negative shock leads to lower collateral value for the borrowers and thereby reduces loan supply. This further depresses demand for the asset and its price, which then reduces access to credit even further.

The endogenous asset price variations are key in generating amplification effects in KM97's model, which are otherwise similar in size to those described in BGG99, yet investment adjustment costs constitute the channel through which price fluctuations are generated in this later framework.

KM97's Framework in more details

In KM97, the economy is populated by two types of infinitely-lived agents of constant sizes and mass $\eta + (1 - \eta) = 1$, both producing the same output good (fruit), but differing in productivity. The more productive agents (farmers) are characterized by a CRS production function yielding $y_{t+1} = F(k_t) \equiv (a + c)k_t$ in period t + 1 for a land input of k_t in period t, and are less patient with a discount factor β such that $0 < \beta < 1$. Only the portion ak_t of this output is tradable in the market, the rest ck_t is consumed by the farmer.⁴ In contrast, the less productive but more patient agents (gatherers) with a discount factor β' such that $\beta < \beta' < 1$, use a decreasing returns to scale production technology which yields only tradable fruit $y'_{t+1} = G(k'_t)$ in period t+1 for an input of k'_t land in period t, with G'(.) > 0 and G''(.) < 0.

Because of their impatience, the productive agents will want to borrow from the less productive ones, yet borrowing is subject to the limited enforcement friction as the lenders ensure that the size of the debt plus interest does not exceed the value of the borrowers' assets holding. This results in the following collateral constraint:

$$Rb_t \le q_{t+1}k_t \tag{2.7}$$

This borrowing constraint means that if at date t a productive agent has capital k_t , then it can borrow b_t in total, as long as the repayment does not exceed the market value of its land at date t + 1, at a constant gross interest rate R.

At each date t, the productive agent's optimal demand for land (or capital) to be used in the production process is obtained as

$$k_t = \frac{1}{q_t - \frac{1}{R}q_{t+1}} \left((a + q_t)k_{t-1} - Rb_{t-1} \right)$$
(2.8)

where $(a + q_t)k_{t-1} - Rb_{t-1}$ is the farmer's net worth at the beginning of time t. The expression $u_t \equiv q_t - \frac{1}{R}q_{t+1}$ can be thought of as the down payment required to purchase a unit of land, that is the margin requirement implied by the borrowing constraint. Besides, as the less productive agent is not credit constrained, its optimal demand for capital is determined at the point where the present value of the marginal product of land is equal to u_t , that is

$$\frac{1}{R}G'(k'_t) = q_t - \frac{1}{R}q_{t+1}$$
(2.9)

which can also be interpreted as the opportunity cost of holding land.⁵

The assets market clearing condition requires that the sum of the aggregate demands (in capital letters) for land by both groups equals the total fixed supply of land \bar{K} , that is $\eta K_t + (1 - \eta)K'_t = \bar{K}$. This market clearing condition together with Equation (2.9) implies the

 $^{^{4}}$ This assumption is a device used by KM97 to ensure that productive agents don't postpone consumption indefinitely.

 $^{{}^{5}}u_{t}$ thus plays a dual role in the model: not only is it the gatherers' opportunity cost of holding a unit of land, but it is also the required down payment per unit of land held by the farmers.

following expression for the farmers' aggregate demand for capital:

$$q_t - \frac{1}{R}q_{t+1} = \frac{1}{R}G'(\frac{\bar{K} - \eta K_t}{1 - \eta}) = H(K_t)$$
(2.10)

Hence, in equilibrium, the margin requirement $(q_t - \frac{1}{R}q_{t+1})$ faced by the productive agents is linked to their demand for assets K_t , and a higher K_t is associated with fewer capital being used in the less productive sector.

Re-arranging the asset's market equilibrium condition (2.10), log-linearising around the deterministic steady state and iterating forward, result in the following expression for which the no-bubbles condition holds:

$$\hat{q}_t = \frac{1}{\xi} \frac{R-1}{R} \sum_{s=0}^{\infty} \frac{1}{R^s} \hat{K}_{t+s}$$
(2.11)

where $\xi > 0$ is the elasticity of the supply of land to the farmers with respect to the opportunity cost, at the steady state. This equation shows how all future changes in assets holdings feed back into the change of today's asset price.

If the constrained productive agents are highly leveraged, an adverse productivity shock that reduces their current net worth constrains their access to credit, forcing them to cut back on investment, which in turn depresses production. Less investment also implies that the opportunity cost of land holding falls and therefore land price drops. Consequently, the value of productive agents' existing land decreases and so does their collateral which depends on the land price. This in turn results in even tighter borrowing constraints, depressing further the amount of loans that they can access. These negative effects propagate the initial shock and persist over the subsequent periods, resulting in further reductions in net worth, land holdings and price.

2.2.2 Extensions and Evaluations

2.2.2.1 Extensions

Models using the Costly State Verification Assumption

The first frameworks that have incorporated financial frictions using the CSV credit market representation in dynamic macroeconomic models are Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997). Bernanke and Gertler (1989) (BG89 henceforth) is the first to formally analyse the relation between borrowers' net worth and credit cost, and how this connection may play a substantial role in business cycle fluctuations. They develop a two-period overlapping generations model that embeds financial frictions along Townsend (1979)'s CSV scheme in order to minimise the agency costs resulting from the asymmetric information problem between borrowers and lenders. As in BGG99, borrowers' net-worth plays a key role in BG89, since higher net-worth is associated with lower cost of external funds. An unexpected negative productivity shock that decreases borrowing firms' net-worth will lower their ability to finance investment projects. This reduction in net worth raises the average cost of external funds, and therefore the costs of new investments are higher. As a consequence, firms cut back on investment, which depresses economic activity and net worth in subsequent periods, thus propagating the effects of the initial shock throughout time.

Carlstrom and Fuerst (1997) (CF97 henceforth) embed the CSV credit market representation in a standard RBC model with infinitely lived agents and different discounting for households and entrepreneurs, that quantitatively accounts for the effects qualitatively analyzed in BG89.⁶

In CF97's framework, adverse shocks that affect entrepreneurs' net worth show strong persistence as in BG89. As in that framework, the endogenous evolution of net-worth also plays an important role in the dynamic responses of the model to shocks. An unanticipated negative productivity shock that reduces entrepreneurs' net worth will exacerbate financial frictions and lead to lower capital, investment and net-worth in future periods. However, key in CF97 is that the drop in the amount of capital caused by lower net worth also leads to a higher price of capital. This increase in price has dampening effects with output response being hump-shaped, which is qualitatively consistent with most empirical findings. In addition, unlike BGG99's framework that more straightforwardly incorporates the asset price channel which is important in generating higher amplifications, changes in the price of capital indirectly affect borrowers' net-worth instead in CF97, resulting in lower amplification effects.⁷

Other frameworks embedding the CSV credit market representation in models featuring the financial accelerator mechanism à la BGG99, include Christiano and Fitzgerald (2003), Christensen and Dib (2008), Nolan and Thoenissen (2009), and Gilchrist and Zakrajšek (2012), among others. In particular, using BGG99's model, Nolan and Thoenissen (2009) analyse shocks

 $^{^{6}}$ Borrowers discount the future more heavily than lenders, implying that the cost of external funds is lower than the cost of internal funds and therefore debt is preferred to internal funds. This also ensures that borrowers do not save enough to make the borrowing constraint irrelevant. 7 In particular, while CF97 assume that the agency problem applies to entrepreneurs who only produce the

^{&#}x27;In particular, while CF97 assume that the agency problem applies to entrepreneurs who only produce the capital good whereas households are the agents that accumulate it, entrepreneurs are instead the agents that hold the capital stock in BGG99 while the creation of new capital is delegated to a separate investment sector.
to the efficiency of the financial sector along with TFP and monetary policy shocks, and show that these financial shocks are an important driver of the United States business cycles. Finally, Gilchrist and Zakrajšek (2012) construct a quantitative DSGE model with BGG99-like financial frictions that highlights the role of credit spreads in GDP and investment fluctuations.

Models with Collateral Constraints

Most of the financial frictions literature development is due to KM97's collateral constraints framework which has been extended in several directions. Some of these extensions show how endogenous developments in housing markets can propagate and amplify the effects of exogenous shocks. In particular, Aoki et al. (2004) analyse the effects of monetary policy shocks on housing investment, house prices and consumption in a setting where houses serve as collateral to reduce borrowing costs. Iacoviello (2005) also applies KM97's collateral constraints scheme in a framework with nominal loans where the credit limit is tied to housing values. Besides, Campbell and Hercowitz (2009) study the impact of the early 1980s deregulation in the US mortgages market in a quantitative DSGE model with financial frictions in the form households' borrowing constraints.

Moreover, Monacelli (2009) shows that a framework with borrowing constraints using durables as collateral, is better than a standard New Keynesian model at matching the positive co-movement of durable and non-durable spending and the important reaction of durable spending to monetary policy shocks. Finally, in a more recent paper, Liu et al. (2013) study the interactions between land prices and business investment, using land as a collateral for firms' access to credit. They identify a shock that drives most of the observed fluctuations in land prices, and show that these fluctuations in land prices strongly co-move with investment, consumption and hours worked.

Finally, financial frictions have also been analysed in open economies' setting. As for borrowing households and firms in closed economy, a country's ability to borrow closely depends on its net worth.⁸ Related references include Huybens and Smith (1998), Calvo and Mendoza (2000), Arellano and Mendoza (2002), and Antras and Caballero (2009). More analyses of the macroeconomic implications of financial frictions in open economy settings can be found in Claessens and Kose (2017).

⁸Obstfeld and Rogoff (2002) argue that the importance of financial frictions is presumably even stronger in open economy since contracts are harder to enforce and information asymmetries are higher. As a result, limited pledgeability of assets and limited verifiability of borrowers' credit quality and actions affect access to international funds.

2.2.2.2 Evaluations

Some studies have cast doubt on the quantitative importance of the BGG99 financial accelerator mechanism and suggested that other channels might be more important. In particular, Chari et al. (2007) analyse the effects of financial and non-financial frictions in a quantitative macroeconomic model for the US, and find that wedges in the labour market account for most of the business cycle variations. Moreover, Meier and Müller (2006) show that financial frictions do not play a significant role in an estimated DSGE model for the US subject to monetary policy shocks.

A similar evaluation of the quantitative importance of financial frictions has been conducted with KM97's like collateral constraints models. In particular, Kocherlakota (2000) shows that the magnitude of the amplification effects induced by collateral constraints models are weak and depend on the underlying economy's parametrization. This last point has also been highlighted by Cordoba and Ripoll (2004) who argue that the amplification mechanism in Kiyotaki and Moore (1997) strongly depends on the model's assumptions. They consider a less stylised model and find that while collateral constraints can amplify unexpected shocks to the economy, the effects of these shocks are small. For instance, a standard share of capital of 1/3 in the production function and an elasticity of inter-temporal substitution of 1 result in almost zero amplification. Large amplifications as those observed in the data only arise as a "knife-edge" type of result: they occur at the combination of a small elasticity (< 0.2) and a large share of capital.

Furthermore, in his survey, Quadrini (2011) also highlights the weak amplification effects of collateral-based financial frictions models, suggesting to focus instead on how these financing constraints affect working capital rather than investment. In particular, a key reason for the weak amplification effects is that most of the financial frictions models affect the transmission of productivity shocks, primarily through the investment channel. Although this has the potential to generate sizeable fluctuations in investment, the effects on the capital stock was much less substantial. Besides, labour which is a complement to capital, does not fluctuate enough to match the data. Therefore, given that in these settings, investment is volatile while capital is not, important fluctuations in investment are unlikely to generate large fluctuations. Empirically however, variations in labour input appear to be an important driver of output volatility. Hence, financial frictions to generate large output fluctuations that are in line with the data, they need to have a direct impact on labour. One way to achieve this is by assuming that firms

need working capital.

Besides, other researchers also argue that the quantitative performance of imperfections associated with credit constraints can be dramatically improved by subjecting the financial frictions models to exogenous disturbances that differ from the standard shocks (i.e., TFP or monetary policy shocks) used thus far in the literature, in the sense that they more directly affect the credit contract. One such work is Jermann and Quadrini (2012) where the collateral constraint is on the firms' physical capital which liquidation value (in case of default) is subject to a random disturbance ξ_t exogenously linked to market conditions. In this setting, the borrowing constraint is given by

$$\xi_t \left(k_{t+1} - \frac{b_{t+1}}{1 + r_t} \right) \ge l_t \tag{2.12}$$

where r is the interest rate on inter-temporal debt b, and l is the amount of intra-temporal loan that pays no interest. Jermann and Quadrini (2012) assume that when a firm defaults on its obligations, the lender(s) can recover the full value of the liquidable capital k with probability ξ , and zero with probability $1 - \xi$. A possible interpretation of the randomness of the disturbance ξ_t could be that the sale of the firm's capital requires the search for a buyer so that ξ can be considered as the probability of finding the buyer. Hence, a stochastic ξ affects the price of capital, and this interacts with the exogenous change in the borrowing limit, leading to high amplification effects.

Other similar frameworks include Christiano et al. (2014) and Iacoviello (2015). Christiano et al. (2014) extend the BGG99 framework by assuming that the volatility of the idiosyncratic risks of entrepreneurs is time-varying. This exogenous disturbance, the "risk shock", is associated with greater investment risks in their framework. Instead, Iacoviello (2015) uses a real estate tied collateral constraint framework in which he models the disturbance as an exogenously triggered redistribution shock through default, that transfers wealth from savers to borrowers. Each of these three shocks is shown to play a substantial role in business cycle fluctuations. As a matter of fact, while Iacoviello (2015) demonstrates that his redistribution shock contributes for two-third of the decline in US private GDP during the Great Recession, Christiano et al. (2014) show that fluctuations in their risk shock account for 60% of the fluctuations in the aggregate US output growth rate. Lastly, Jermann and Quadrini (2012) find that the random disturbance ξ_t contributes for almost half to the US output volatility.

Finally, financial frictions can also generate large economic fluctuations that are consistent

with the business cycle, by assuming that collateral constraints only bind occasionally. As a consequence, an adverse shock results in greater amplification mechanisms and asymmetric effects that are not observed in always binding collateral constraints models. Papers in this category include Brunnermeier and Sannikov (2014) and Guerrieri and Iacoviello (2017), among others. In particular, Guerrieri and Iacoviello (2017) estimate a DSGE model with collateral constraints that display asymmetric responses to house price changes. In their model, collateral constraints become slack when housing wealth is high, with positive house price shocks leading to small and positive changes in consumption and hours worked. However, collateral constraints bind when housing wealth is low, with adverse shocks to house prices translating into negative and large changes in consumption and hours worked. Brunnermeier and Sannikov (2014) features occasionally binding borrowing constraints which are essential in producing highly non-linear and asymmetric dynamics intended to capture crisis periods or downturns. In their setting, normal times are characterised by relative stability with slack borrowing constraints and the economy not deviating much from its steady state. However, following a large enough negative shock or a sequence of small disturbances, the economy is drawn into a region where borrowing constraints become binding, exacerbating the effects of the initial shock. Finally, financial frictions with occasionally binding borrowing constraints are also prevalent in the international macroeconomics literature that focuses on sudden stops to capital in-flows in developing countries (Mendoza (2010), Bianchi (2011), etc.). Notably, Mendoza (2010) shows in a setting with occasionally binding borrowing constraints and highly leveraged borrowers, adverse shocks are amplified and have a large impact on output, which helps to explain the the rapid slowdowns or reversals of capital in-flows observed in the developing economies.

2.3 Models with Supply-side Financial Shocks

Up to now, the central idea of the propagation of adverse shocks by financial frictions is that these shocks first arise in the non-financial or real sector of the economy, caused for example by a drop in productivity as in most of the papers surveyed in the previous section. Instead, this section covers models with financial shocks which occur directly in the financial sector with frameworks that explicitly incorporate financial intermediaries. This strand of the literature assumes that the initial adverse shock stems from the supply side of credit, causing fewer funds to be channelled from lenders to borrowers. In particular, there is a large consensus on widespread evidence of the disruption in the supply of credit intermediated by banks and other financial intermediaries during the last crisis. In particular, Tobias et al. (2012) show that disruptions in the financial intermediation process during the crisis played a central role in exacerbating the related recession.

Depending on the nature of the disturbances, these supply-side financial shocks frameworks can be subdivided into three categories. The first category gathers models where the exogenous shock primarily affects banks' balance-sheets. Hence, just as is the case of borrowers, lenders' operations can also be affected by variations in their net worth or capital. The second category of models deals with factors other than banks' balance-sheets strength, that directly affect banks' lending behaviour, such as risk appetite or competition pressure, and may thus help propagate related supply-side shocks. Finally, the third group of works highlights the possibility that supply-side shocks may arise from sharp variations in banks' liquidity through the inter-bank market and when banks are subject to runs, or may stem from shadow banking as during the last crisis.

2.3.1 Banks' Balance-sheets Strength

I first analyse the implications of changes in banks' balance-sheets conditions for the real economy. Shocks to banks' balance-sheets can be any forms of disturbances that directly weaken or strengthen banks' capital: e.g., changes in regulatory measures that require banks to hold higher capital buffers may lead them to adjust their lending activities if they cannot raise funds quickly.⁹

Works of the post-crisis period that analyse the quantitative implications for economic activity of changes in banks balance-sheets include Gertler and Kiyotaki (2010), Gerali et al. (2010), and Meh and Moran (2010) among others. In particular, Gertler and Kiyotaki (2010) develop a model that exhibits moral hazard in the financial sector when banks issue deposits to households and borrow on the interbank market, thus providing a role for bank capital.¹⁰ Importantly, there is an agency problem that restricts the ability of banks to raise funds from depositors and on the interbank market. Due to moral hazard, there is an incentive-compatibility constraint that prevents banks from diverting the funds that they receive from the lenders and defaulting. In the case of default however, depositors can only recover a fraction $(1 - \theta)$ of their deposits and lenders on the interbank market only recover $(1 - \theta(1 - \omega))$, with $0 \le \omega \le 1$. The

⁹This is opposed to the so-called bank balance-sheets channel, also referred to as the bank lending channel or the narrow credit channel, which is a transmission mechanism traditionally identified in the literature as being particularly relevant for the propagation of monetary policy shocks.

 $^{^{10}}$ A similar framework is used in Gertler and Karadi (2011) to assess the Fed's unconventional monetary policy.

incentive-compatibility constraint to ensure that a given bank does not divert funds is given by:

$$V_t(s_t^h, b_t^h, d_t) \ge \theta(Q_t^h s_t^h - \omega b_t^h)$$

$$(2.13)$$

where $V_t(.)$ is the present value of the bank's expected future dividends and $Q_t^h s_t^h$ the value of loans funded within a given period which must equal the sum of the bank net worth n_t^h , its borrowing on the interbank market b_t^h and the deposits d_t raised from households, that is $Q_t^h s_t^h = n_t^h + b_t^h + d_t$. An increase in θ and/or a decrease in ω following a sharp deterioration of the intermediaries' balance sheets, will lead to tightened margins as lenders restrict credit.¹¹

In Gerali et al. (2010), the credit supply shock that weakens intermediaries balance-sheets takes the form of an unexpected destruction of bank capital which leads to a decrease in consumption and investment through the financial accelerator mechanism, and therefore results in lower production. Finally, Meh and Moran (2010) develop a framework with moral hazard in the spirit of Holmstrom and Tirole (1997) and Chen (2001), where adverse changes in the capital position of banks impair their ability to attract loanable funds and lead to sizeable declines in output and investment.

2.3.2Banks' Lending Behaviour and Leverage Cycle

This sub-section analyses the role of bank lending behaviour in shaping macroeconomic outcomes. Factors that affect bank lending behaviour include banks' risk appetite, competition pressure, and the riskiness of borrowers (namely small firms and households). In particular, banks' risk taking behaviour may lead to the build-up of bank leverage (defined as the ratio of total assets to shareholders' equity), fed by looser credit conditions as during the period following the 1980's financial markets deregulation.¹²

Papers that analyse the importance of banks' risk taking behaviour in their lending decisions include Disyatat (2011), Gertler et al. (2012), and Borio and Zhu (2012) among others. Notably, Gertler et al. (2012) extend Gertler and Kiyotaki (2010) to allow banks to issue outside equity in addition to short term debt. Their model predicts that excessive bank risk exposure increases the occurrence of financial crises, and can also help to explain why banks adopt such build-up

¹¹In particular, Gertler and Kiyotaki (2010) consider an exogenous decline in bank capital quality, notably a 5% unanticipated decline with an autoregressive factor of 0.66 so that it produces a downturn similar in magnitude to the one observed during the 2008-2009 financial crisis. ¹²The reader interested in recent works of the post-crisis period that embed leveraged financial institutions into

DSGE models with the objective of analysing financial crises, can refer to Duncan and Nolan (2018).

of leverage in the first place. They then use the model to study the effects of macro-prudential policies aimed at offsetting the incentive for risk taking.

2.3.3 Interbank Market Freezes, Bank Runs, and Shadow Banking

Credit supply-side shocks may also arise from stark variations in banks' liquidity either through the interbank market or when banks are subject to runs, or through the role of shadow banks.¹³ In particular, an adverse shock in the form of a frozen inter-bank market that disrupts liquidity provision and loan supply more generally, pushes less liquid banks to raise cash by selling illiquid assets. This increases asset price volatility and leads to liquidity hoarding, thus exacerbating the initial negative shock. Works that highlight the role of the inter-bank market include Gertler and Kiyotaki (2010), Gertler et al. (2016), and Boissay et al. (2016) among others.¹⁴

In particular, Gertler and Kiyotaki (2010) introduce an interbank market in their framework by assuming that some banks have excess funding liquidity whereas others are experiencing a shortage of funds. Yet, because of financial frictions, it is costly to reallocate funds from excess liquidity banks to lower liquidity ones. The authors show that such frictions in the interbank market adversely affect the real economy compared to a no-interbank friction benchmark which does not distort real activity. Besides, building on Gertler and Kiyotaki (2010), Gertler et al. (2016) extend the core DSGE framework to include shadow banking, and show that in an equilibrium with runs, shadow banks sell off loans, which puts a downward pressure on asset prices and deteriorates bank balance-sheet, impairing their ability to extend loans to borrowers.

Another key recent work that incorporates the interbank market in a macroeconomic model is Boissay et al. (2016) which studies the frequency of financial crises in a framework where an interbank market subject to an Akerlof lemons problem is central to the analysis. Importantly, a bank's type is private information in their setting. Periods of downturns that push households to increase savings for consumption smoothing and firms to borrow less owing to future lower demand, lead to higher net savings which depress interest rates overall, including on the interbank market. With a lower interbank rate, less efficient banks are more tempted to borrow and divert funds, and since bank type is private information, the interbank market becomes risky and lending declines accordingly, reflecting the lemons problem. In particular, Boissay et al. (2016) show that

 $^{^{13}}$ For a detailed review of the recent literature that analyses the role of interbank market, bank runs, and shadow banking in financial crises, see Duncan and Nolan (2018).

 $^{^{14}}$ For an empirical work on the role of the interbank market in the recent crisis, one can refer to Gorton and Metrick (2012) which emphasizes the role of securitization in the repo market.

there is a threshold interest rate under which the interbank market freezes, resulting in credit crunch with a subsequent deep recession.

Finally, there is the strand of the literature that incorporates insights from Diamond and Dybvig (1983)'s bank runs into macroeconomic models with financial frictions. Banks special role in maturity transformation by both investing in long-term projects and issuing short-term debt claims, exposes them to "liquidity mismatch" (Brunnermeier and Sannikov (2016)), which results in fragility. This fragility then unfolds in runs, especially if banks are also exposed to aggregate risk. In turn, the adverse bank runs shock dries up liquidity, hindering banks' liquidity provision function and disrupting extension of loans to borrowers. In particular, Building upon Gertler and Kiyotaki (2010), Gertler and Kiyotaki (2015) develop a DSGE model that features both financial accelerator effects and bank runs, and show that a banks run equilibrium in crisis time disrupts credit intermediation and weakens economic activity.

2.4 Models with Demand-side Financial Shocks

This section surveys the growing literature on debt (de-)leveraging, where financial shocks rather arise from the demand side of credit in the form of an exogenous disturbance that pushes borrowers to lever-up or de-lever, leading to business cycle fluctuations through a channel different from the financial accelerator propagation mechanism highlighted in the two previous sections above and where changes in credit demand only occur endogenously.

Yet, I start by presenting some evidence of credit demand shocks based on the recent US business cycles. Then I construct a simple two-period model highlighting the interactions between borrowers and lenders on the credit market to provide some insights of shifts in the credit demand curve in partial equilibrium, and finally analyse the growing debt (de-)leveraging literature.

2.4.1 Credit Demand Shocks: Evidence from the Aftermath of the Great Recession

In this section, I present some facts of pure credit demand disruptions through the slow recovery observed in the aftermath of the Great Recession in the US, with households voluntarily deleveraging on their debts rather than being forced to do so by credit suppliers.



FIGURE 2.1: Households' Voluntary Deleveraging

Note: This figure reports the responses of financial and macroeconomic variables to an negative loan supply shock. Credit supply shocks mostly propagate to the economy through the Financial accelerator mechanism.

As can be seen from the upper panels of FIGURE 2.1 above (red curves only), the aftermath of the recession broadly coincides with a protracted period of a substantial reduction in household debt, both in terms of extensive and intensive margins. Although this deleveraging may be a consequence of credit demand (i.e., households willing to borrow less) or supply (banks tightening access to credit), it is usually attributed to the latter.

In order to understand whether this deleveraging was caused by a contraction in credit demand or supply, I connect the deleveraging process with the evolution of household financial distress. For that I use three measures of household financial distress: the proportion of households with debt-payments-to-income ratio greater than 40%, the 90+ days delinquency rate on household mortgage debt (i.e., the proportion of households with mortgage debt payments 90 days or more late), and the number of households with new forclosures and bankruptcies.¹⁵ I retrieved these measures of financial distress from the US Survey of Consumer Finances (SCF) triennal series, as well as quarterly data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax.¹⁶

¹⁵Forclosure is the action of taking possession of a mortgaged property when the mortgagor fails to keep up their mortgage payments.

 $^{^{16}{\}rm Equifax}$ is a consumer credit reporting agency that collects (and aggregates) information on over 800 million individual consumers and more than 88 million businesses worldwide.

If the deleveraging were caused by tightened debt limits, one should expect a rise in household financial distress because households would have difficulty rolling over their current obligations. In contrast to that prediction, as one can see from the graphs, household financial distress as measured by the three indicators, decreases during this period. Besides, the lower-right panel of the figure also shows that the post-crisis deleveraging did not drive more households into financial distress (as measured by the decreasing number of new forclosures and bankruptcies). Together, those two previous arguments suggest that households were not forced to reduce borrowing but

Hence, this evidence points at negative credit demand shocks, i.e., a fall in loan demand through household voluntary deleveraging, and not a tightening of access to credit from lenders.

instead decided to do so in light of the related developments, in line with Di Maggio et al. (2017).

2.4.2 A Simple two-period Model of Credit Demand Shocks

Given the previous illustration of credit demand shocks, I now build a simple two-period model highlighting the interactions between borrowers and lenders on the credit market as well as credit demand and supply schedules. This model will then serve to analyse how an unexpected loan demand shock (through a sudden change in the borrower's loan-to-value parameter as explained further below) shifts the loan demand curve for a given loan supply schedule.

Setting and Assumptions

I consider an incomplete markets two-period endowment economy with two types of agents, borrowers and savers, which differ in terms of time preference. Borrowers are more impatient than savers, i.e. $\beta_b < \beta_s$, β_b and β_s being the discount factors of borrowers and savers, respectively. Both types of agents start out with zero saving, yet borrowers initially hold an illiquid asset k. Savers are endowed with income y_s in period 0 and y'_s in period 1, whereas borrowers receive no income endowment in period 0, and y'_b in period 1. Hence, borrowers must borrow from savers in period 0 in order to consume, using their illiquid asset as collateral. The only financial instrument available to the agents in this economy is a nominal bond. Debt is therefore in nominal terms, as are most of the financial contracts in the economy, and are not indexed against unanticipated movements in the general level of prices. Borrowing and lending between the two types of agents is motivated by both the cross-section difference in the rate of time preference (as $\beta_b < \beta_s$), and the different income timing described above providing an incentive for inter-temporal trade.¹⁷

The Savers

The representative saver maximizes its inter-temporal utility

$$U(c_s) = \log(c_s) + \beta_s \log(c'_s)$$

subject to the following period-by-period budget constraint:

$$c_s = y_s - d_s \tag{2.14}$$

$$c'_{s} = y'_{s} + \frac{(1+r)}{\pi'} d_{s} \tag{2.15}$$

where c and y are consumption and income endowment respectively, d_s is the amount of lending to borrowers and (1+r) denotes the gross nominal interest rate on this loan. In addition, the interest rate is endogenously determined in the model. π' is future gross inflation rate, so that $\frac{(1+r)}{\pi'}d_s$ denotes period 1 gross income on loans in real terms.

The combination of equations (2.14) and (2.15) yields the following inter-temporal budget constraint for the saver:

$$c_s + \frac{c'_s}{1+r} = y_s + \frac{y'_s}{1+r} + \left(\frac{1}{\pi'} - 1\right)d_s$$
(2.16)

Solving the saver's inter-temporal utility maximization problem results in the following standard Euler equation:

$$\frac{1}{c_s} = \beta_s \frac{(1+r)}{\pi'} \frac{1}{c'_s}$$
(2.17)

Rearranging equation (2.17) to get $c_s = \frac{\pi' c'_s}{\beta_s (1+r)}$, and substituting this into equation (2.16) yields

$$\left(\frac{\pi'}{\beta_s} + 1\right)\frac{c'_s}{1+r} = y_s + \frac{y'_s}{1+r} + \left(\frac{1}{\pi'} - 1\right)d_s \tag{2.18}$$

Then, the substitution of c'_s expression from equation (2.15) into (2.18) and some algebra lead to the following upward-sloping loan supply schedule:

 $^{^{17}}$ Koenig et al. (2013) combines income timing differences across agents with uncertainty about future income to motivate risk sharing in a two-period setting where the focus is on analysing the monetary policy implications of risk distribution between borrowers and lenders.

$$1 + r = \frac{-\pi' y'_s}{(1 + \beta_s) d_s - \beta_s y_s} \tag{2.19}$$

Equation (2.19) implies that savers are willing to supply higher levels of loans at higher interest rates, for any given level of future inflation. Therefore, one could set $\pi' = 1$ without loss of generality.

The Borrowers

The representative borrower maximizes its inter-temporal utility

$$U(c_b) = log(c_b) + \beta_b log(c'_b)$$

subject to the following period-by-period budget constraint:

$$c_b + qk = d_b \tag{2.20}$$

$$c'_{b} = y'_{b} + q'k - \frac{(1+r)}{\pi'}d_{b}$$
(2.21)

where the borrower only receives an income endowment y'_b in period 1, and its illiquid asset k in fixed supply has resale value q'k, with q and q' taken as given. This implies the following inter-temporal budget constraint:

$$c_b + \frac{c'_b}{1+r} = \frac{y'_b}{1+r} + \left(\frac{q'}{1+r} - q\right)k + \left(1 - \frac{1}{\pi'}\right)d_b$$
(2.22)

The borrower is also subject to the following borrowing constraint:

$$d_b \le mq'k \tag{2.23}$$

where d_b is the amount that the borrower must borrow in period 0 where it has no income endowment, using its illiquid asset as collateral. Of course, this zero initial income endowment assumption for borrowers just serves to provide an extra motive for credit demand, and is in no way essential to the main conclusion of this analysis. Variations in the loan-to-value (LTV) parameter m are interpreted as credit demand shocks, i.e., exogenous changes that induce the borrower to take on more or less debt. It is worth emphasizing that this interpretation of changes in m as loan demand shocks differs sharply from the common interpretation of variations in these LTVs as inducing higher or lower credit supply by lenders, based on borrowers perceived riskiness.¹⁸ These later credit supply disturbances are the shocks perturbing the economy in

 $^{^{18}{\}rm Hence},$ LTV shocks can equally be interpreted as credit supply or credit demand shocks, depending on the underlying analysis.

most collateral constraints models through the financial accelerator channel.

The borrower's maximization problem implies the following Euler equation:

$$\frac{1}{c_b} = \beta_b \frac{(1+r)}{\pi'} \frac{1}{c'_b} + \lambda$$
(2.24)

where $\lambda \geq 0$ is the Lagrange multiplier on the borrowing constraint. Equation (2.24) states that the marginal utility $\frac{1}{c_b}$ from the borrower's current consumption (in period 0), is at least as high as its marginal utility $\frac{(1+r)}{\pi'} \frac{1}{c'_b}$ from saving for the future (period 1). In particular, when the borrowing constraint is binding (i.e., $\lambda > 0$), the borrower's marginal utility $\frac{1}{c_b}$ from current consumption exceeds its marginal utility from saving for next period.

Furthermore, when the borrowing constraint is not binding (i.e., $\lambda = 0$), using equations (2.22), (2.24) and (2.21) as before, yields the following downward-sloping loan demand schedule, after some algebra:

$$1 + r = \frac{\pi'(y_b' + q'k)}{(1 + \beta_b)d_b - \beta_b qk}$$
(2.25)

When the constraint is binding, the loan demand curve becomes vertical:

$$d_b = mq'k \tag{2.26}$$

Equation (2.25) implies that borrowers are willing to request more loans at lower interest rates, for any given level of future inflation. One could, again, set $\pi' = 1$ without loss of generality.

Equilibrium and Comparative Statics

The credit market clearing condition is $d_b = d_s$ (= d), implying equilibrium interest rate and debt level of respectively

$$1 + r = \frac{\pi'[(1+\beta_s)(y'_b + q'k) + (1+\beta_b)y'_s]}{\beta_s(1+\beta_b)y_s - \beta_b(1+\beta_s)qk} \quad \text{and} \quad d = \frac{\beta_s y_s(y'_b + q'k) + \beta_b y'_s qk}{(1+\beta_s)(y'_b + q'k) + (1+\beta_b)y'_s}$$

when the constraint is slack, and

$$1 + r = \frac{\pi' y'_s}{\beta_s y_s - (1 + \beta_s) mq' k}$$
 and $d = mq' k$ when the constraint is binding

Importantly, from the above expressions, on can see that variations in m do not affect the equilibrium interest rate and debt when the borrowing constraint is slack since both do not contain m, whereas shifts in m matter when the constraint is binding with a higher m resulting in

an upward shift of the loan demand schedule and higher equilibrium interest rate and borrowing, all things else equal.^{19,20}

Besides, higher future inflation leads to higher equilibrium interest rate, all things else being equal, and irrespective of whether the borrowing constraint is binding or not. Intuitively, lenders increase interest rates to off-set the lower returns on their loans resulting from a reverse Fisher deflation channel which works through the higher price levels.

I now turn to provide a simple illustration in partial equilibrium of how loan demand shocks, i.e., variations in the parameter m, shift the credit demand curve (obtained by combining equations (2.25) and (2.26) above) for a given loan supply schedule (equation (2.19)).



FIGURE 2.2: Illustration of Credit demand Shocks when Borrowing Constraints Bind

Note: This figure illustrates the shifts in the credit demand curve for a given credit supply schedule, in a credit market with financial frictions where borrowers are constrained by the amount of loans that they can obtain from lenders. These borrowing constraints can take the form of exogenously fixed debt limits or collateral constraints.

In FIGURE 2.2 above, a credit demand shock in the form of an exogenous change in the parameter m that induces borrowers to lever up or de-lever, leads to upward or downward shifts of the loan demand curve CD_0 along the loan supply curve CS_0 , resulting in new equilibria characterised by the co-movement of credit quantity and price. In particular, an adverse credit demand shock, that is a fall in m, shifts the credit demand schedule to the left from CD_0 to

¹⁹The irrelevance of loan demand shocks for slack borrowing constraints is also highlighted in Maffezzoli and Monacelli (2015). ²⁰In this case, it is optimal for borrowers to borrow up to the debt limit mq'k.

 CD_1 , resulting in a new equilibrium at point A_1 , with both a lower interest rate and lower debt level. Intuitively, by triggering a fall in the demand for debt, this negative loan demand shock generates an excess supply of debt, all things else being equal. The interest rate therefore needs to drop in order to re-establish the equilibrium in the credit market. A similar mechanism is at play in the event of a positive loan demand shock, which shifts the credit demand curve to the right along the credit supply curve, resulting in a new equilibrium at A_2 with higher debt and interest rate.

Overall, the analysis of this simple two-period economy of borrowers and lenders helped to uncover important features of nominal debt when the economy is subject to loan demand shocks. The variations in the equilibrium interest rate linked with price level fluctuations and the Fisher deflation channel highlighted above, provide key insights on the transmission mechanisms of exogenous loan demand shocks to the economy. This Fisher channel is also presented as the key mechanism through which adverse loan demand shocks propagate to the real economy in the debt deleveraging literature below.

2.4.3 The Current Debt Deleveraging Literature

The unprecedented leverage cycle around the Great Recession has drawn the attention of researchers to the connection between household debt and the macroeconomy. A growing literature attempts to explain to what extent and through which channels the excessive build-up of household debt and the protracted deleveraging that followed might have contributed to depressing economic activity and consumption growth in the aftermath of the crisis.

2.4.3.1 Macroeconomic Settings

Key theoretical contributions include Guerrieri and Lorenzoni (2017) and Eggertsson and Krugman (2012) that modelled the idea that an unexpected negative shock to consumers' ability to borrow forces them into rapid deleveraging, which if large enough, pushes the economy against the zero lower bound (ZLB), thus exacerbating recessions and delaying recoveries. The adverse effects are larger if debt takes the form of nominal obligations, as Fisherian debt deflation magnifies the effects of the initial shock. While Guerrieri and Lorenzoni (2017) adopt Aiyagari (1994)'s assumption of motivating borrowing and lending with uninsurable idiosyncratic shocks in order to capture precautionary effects in a setting with heterogeneous agents, Eggertsson and Krugman

(2012) instead assume that borrowing and lending is motivated by difference in preferences of the two types of agents, i.e., difference in their impatience to consume.

Quantitative works have been undertaken to evaluate these theoretical predictions. One key such works is Justiniano et al. (2015b) who add a quantitative perspective on the causes and consequences of the exceptional US household leverage cycle which occurred around the Great Recession period. They build a calibrated DSGE model where debt limit is endogeneously tied to the market value of collateral housing assets, and find that household deleveraging in isolation is not a strong enough force to account for the large contraction in economic activity and the slow recovery from the Great Recession. This is partly due, they argue, to borrowers and lenders reactions "washing out" in the aggregate.²¹

A similar conclusion has been reached by Philippon and Midrigan (2011) who propose a framework in which liquidity constraints amplify the response of employment to changes in debt. They find that a 25% decline in household debt as observed at the onset of the Great Recession, leads to a modest 1.5% drop in the natural rate of interest, and is easily offset by monetary policy without triggering the ZLB. Because of this, household credit shocks alone generate a modest, 1.4% drop in employment. However, household deleveraging turns out to be more important in the presence of other shocks that trigger the ZLB on the policy rate, accounting for about half of the decline in US employment.

Finally, Caggese and Perez (2015) develop a general equilibrium model with heterogeneous households and firms that face uncertainty and are subject to financial frictions. They show that household deleveraging shocks and credit shocks to firms interact and amplify each other when they occur simultaneously, generating large drops in output and employment, thanks to a dynamic feedback between the precautionary behaviour of households and firms. In isolation however, each of these shocks has only moderate effects on GDP and unemployment. Their results also support the view that firm financial frictions are important to understand the effects of household deleveraging on unemployment.

2.4.3.2 Microeconomic Settings

Moreover, there have been some works on the effects of household deleveraging in partial equilibrium and microeconometric settings. These include Mian and Sufi (2010), Mian and Sufi

 $^{^{21}}$ Borrowers and lenders react in opposite ways to the shocks that cause the leverage cycle. When borrowers delever and cut their consumption, lenders do exactly the opposite. Qualitatively, this behaviour is not surprising in this class of models.

(2011), Mian et al. (2013) and Mian and Sufi (2014) who document that rising house prices in the years prior to the Great Recession led to the build-up of household leverage, causing a sharp drop in consumer demand as house prices plummet during the crisis. In particular, they use geographic variations to argue that US counties in which households were more heavily indebted relative to their income (i.e., those counties that experienced a large increase in household leverage) during the crisis, also experienced sharper declines in consumption expenditure and employment. These findings suggest that a focus on household finance may help elucidate the sources of macroeconomic fluctuations.

Other contributions on deleveraging at regional level using micro data include Giroud and Mueller (2017), and Di Maggio et al. (2017). Di Maggio et al. (2017) highlight borrowers' voluntary deleveraging behaviour using US mortgage data with adjustable rates.²² In particular, they argue that low adjustable-rate mortgages (ARMs) rates following the Fed accommodating monetary policy have pushed households to reduce the burden of their debt through voluntarily deleveraging. Notably, they show that households use more than 10% of the increase in their disposable income following the decrease in ARMs rates to repay their debts more quickly. They also document significant heterogeneity in borrowers' responses to ARMs rate reductions depending on their income and wealth. Specifically, they show that low-housing wealth (i.e., high loan-to-value) and low-income households tend to consume significantly more and deleverage less than low loan-to-value and high-income ones in response to the rate reduction.

Giroud and Mueller (2017) highlight the key role of firm balance-sheets in the transmission of consumer demand shocks during the Grate Recession. Using micro-level data from the U.S. Census Bureau and Compustat, they show that more highly levered firms at the onset of the recession experienced significantly larger employment losses in response to a decline in local consumer demand. They also find that more highly levered firms found it more difficult to raise additional debt following a decline in local consumer demand. As a consequence, these firms experienced more lay-offs, cut back more on investment, and were more likely to shut down.

All these micro data-based findings suggest that any realistic macroeconomic framework of the Great Recession and its aftermath must be consistent with the time-series and cross-sectional patterns documented in these works.

 $^{^{22}}$ In section 2.4.2.3 below, I present supporting evidence on voluntary deleveraging in the aftermath of the Great Recession, in line with Di Maggio et al. (2017).

2.5 Conclusion

This survey analysed the importance of non-financial and financial shocks for economic fluctuations in macroeconomic models with financial frictions. I first reviewed how financial frictions frameworks that feature TFP, preference or other non-financial shocks result in business cycle fluctuations through the financial accelerator mechanism. Then I highlighted how the post-2008 financial crisis models that directly incorporate financial shocks in settings with financial intermediaries, lead to higher economic fluctuations in line with the data, compared with the first generation of financial frictions models of the pre-crisis period.

In the post-crisis literature, I distinguish between financial shocks that originate from the supply side of credit and those originating from the demand side. Models with supply-side shocks include settings with financial shocks triggered by sharp changes in banks' balance-sheets, settings with shocks directly affecting banks' lending behaviour, and more recent frameworks with shocks that primarily stem from sharp variations in banks' liquidity either through bank runs, the inter-bank market, or shadow banking. Settings with demand-side financial shocks are characterised by exogenous disturbances that induce borrowers to voluntarily lever-up or de-lever, resulting in amplification effects on the economy through a Fisher debt-deflation channel.

Whereas the supply-side literature extensively grew since the crisis, works that analyse both the effects for economic activity and the policy implications of demand-side financial shocks are quite scant. The next two chapters attempt to reduce the gap by proposing an empirical and structural analysis of the importance of credit demand shocks for the macroeconomy.

Chapter 3

Comparative Analysis of Credit Supply and Demand Shocks

This paper evaluates the relative effects of credit demand and supply shocks on economic fluctuations using UK data. To tackle the identification problem, we use the unique Bank of England's credit conditions survey data that allow us to construct loan supply and demand variables, which we then combine with standard macroeconomic variables to account for the linkages between the credit and the business cycles. We carry out this analysis in a structural vector auto-regression (SVAR) setting where credit supply and demand shocks are identified using a combination of zero and sign restrictions, and estimate the model using Bayesian methods. We find that not only are credit demand shocks important for economic fluctuations, but also that they are as important as credit supply shocks for the UK economy. This result is at odds with the common belief that credit demand shocks are not relevant for the business cycle and therefore should not retain policy makers' attention. The finding is robust to several alternative specifications, including the inclusion of additional control variables, the use of alternative definitions and proxies for the credit variables, the estimation of the model with flat priors, the use of alternative identifying assumptions, and the assignment of arbitrary weights to the different types of loans. We also find that the UK economy, when subject to credit supply and demand shocks in a heterogeneous loan-types setting that includes business, mortgage and consumer loans, is significantly driven by the mortgage loans market.^{1,2}

¹This is a joint work with two of my supervisors: Alessandro Mennuni and Michael Hatcher. As the main author of the paper, I gathered a comprehensive literature on the topic, formulated the research question, proposed the methodological approach and identified the relevant data to address it. I also performed the quantitative analyses and wrote the paper's draft. Yet, I greatly appreciate the efforts Alex and Michael invested in this paper to improve its quality throughout the project.

²The paper also benefited from comments and suggestions from seminar and conference participants at Southampton, the 2018 International Association for Applied Econometrics (IAAE) annual conference in Montreal, and The 2018 International Conference on Economic Modeling (ECOMOD2018) in Venice.

3.1 Introduction

There exists an extensive literature on credit supply channels that analyses the effects of loan supply-side disturbances on the economy.³This literature generally considers that these loan demand shocks are economically non-significant enough to be analysed, or points at identification challenges or data availability on the demand side of the credit market. However, the recent Great Recession has drawn attention to credit demand shocks and the accompanying deleveraging process as key potential explanations for the sluggish recovery observed in the US and the UK in the aftermath of the crisis. Moreover, with the growing availability of new survey data sets from central banks on credit demand and supply schedules, we not only need to analyse the importance of credit demand shocks for economic fluctuations, but also to understand the related policy implications. In particular, thanks to the Bank of England (BoE henceforth) Credit Conditions Survey (CCS thereafter) that collects quarterly data on changes in loan supply and demand, we are able to adequately analyse the demand side of the credit market.

Yet, we remain agnostic as for what causes credit demand or supply shocks, except that they occur as unexpected exogenous changes in loan supply or demand. Whereas an adverse credit supply shock results in both tightening of loan quantities and/or increased lending rates by the lenders, a negative credit demand shock instead leads to a contraction in both loans volume and interest rates. For loan supply shocks in particular, the exogenous changes can be linked to events such as a higher collateral requirement from lenders because of the riskiness of borrowers, a change in the degree of competition in the banking sector, a change in the risk taking behaviour of banks, or an unexpected change in financial regulations. For instance, the financial stability authority may impose higher capital requirement on banks or other regulatory constraints on lending. Instead, credit demand shocks can be associated with events such as a decreased or increased confidence in future expected income streams or investment opportunities, and more generally to optimism or pessimism about the future economic outlook. Loan demand disturbances could also stem from a voluntary deleveraging process due for instance to a downward adjustment of mortgages rates as witnessed in the US following the accommodating monetary policy by the Federal Reserve in the aftermath of the Great Recession.

Furthermore, the investigation of the effects of credit demand shocks for the economy may have important policy implications. First, because a recessionary credit supply crunch does not imply the same policy response as its demand counterpart, an adequate analysis of whether

³Related theoretical works go back to Kiyotaki and Moore (1997) and Bernanke et al. (1999), and include Curdia and Woodford (2010), Christiano et al. (2010), Gerali et al. (2010), Gertler and Karadi (2011), and Jermann and Quadrini (2012) among many others.

a given recession was caused by a credit demand or supply shock may help to formulate the appropriate policy action. For instance, expansionary monetary policy directed at easing credit availability may be effective in response to a contractionary credit supply shock but less so if the disturbance originated on the demand side. Second, distinguishing between credit demand and supply shifts may help identify other shocks originated in other sectors of the economy because such shocks may affect credit demand and supply differently. For example, since changes in loan supply and demand depend on both endogenous and exogenous factors, the policy maker is interested in disentangling whether the credit market is the source of the disturbances or acts as a propagator of shocks originated in other sectors of the economy.

Moreover, in its aim for price stability, the central bank generally relies on the pass-through of its policy rate to retail interest rates charged by banks on borrowing firms and households. Adjustments to the monetary policy rate (or, equivalently to the monetary base) would thus feed through similar changes in the lending interest rates, leading to more or less borrowings for consumption and investment expenditures, which would ultimately affect the general level of prices. Finally, while the central bank has a better understanding of how its policy could affect banks and other creditors (through these credit suppliers' balance-sheets and other records that it collects), it however has much less control over credit demand shocks. For instance, even though the BoE conducts the CCS and other surveys that help her to understand households and firms loans demand behaviours up to some extent, she still has much more data and experience when it comes to the design of policies that affect the supply side of the credit market. Therefore, using the CCS to infer how credit demand shocks affect the economy seems a good starting point which may help the BoE to formulate adequate policies that influence changes in loan demand by firms and households.

Against this background, our main objective is to assess whether credit demand shocks are more or less important than credit supply shocks for economic fluctuations. In particular, we are interested in answering the following question: how does the economy respond to unanticipated exogenous changes in loan supply compared with similar changes in loan demand? We address this question by analysing the effects of each of these exogenous credit shocks on key macroeconomic variables, namely GDP and prices, in a vector auto-regression (VAR) setting applied to UK data. Yet a recurrent issue with these types of analysis is to ensure that one appropriately identifies each of the shocks of interest.

Uniquely identifying and disentangling the effects of credit demand and supply shocks is challenging because of various potential forms of endogeneity problems. One of these endogeneity challenges is the simulataneity issue according to which changes in credit supply and demand reflect the confluence of both demand and supply factors, so that each of these credit shocks simultaneously affects loan demand and supply, making it more difficult to disentangle their individual effects on credit growth and in fine on economic activity. For example, bank-specific factors such as changes in banks market shares objectives or risk taking behaviour, which systematically influence their lending policies and hence loan supply, are also very likely to affect loan demand as well. This simultaneity challenge is generally overlooked in the literature that analyses the effects of credit shocks for economic fluctuations.⁴

A second form of endogeneity which is more commonly addressed, stipulates that the same macroeconomic and financial factors that influence loan supply by banks also affect loan demand from households and firms. These factors include changes in the stance of monetary policy, in the general economic outlook, in borrower or lender specific factors, and disturbances to aggregate supply and aggregate demand. For instance, a change in the stance of monetary policy will affect both lending and borrowing.⁵ In particular, an increase in the policy rate may directly result not only in higher interest rates charged by banks that also incur increased funding costs, but also leads to households and firms reducing their borrowings because of the higher lending rates. In addition, the higher policy rate may have an indirect effect on consumption and investment spending as well as production, through its influence on expectations.

To overcome these challenges and adequately identify credit demand and supply shocks, we use the BoE's CCS data that allow us to construct loan supply and demand variables in a first step. These novel survey data on credit demand and supply schedules allow us to separately identify loan demand and supply shocks. Then, we combine the constructed credit variables with macroeconomic variables to account for the linkages between the credit and the business cycles in the VAR model. We carry out this analysis using a structural VAR framework where credit supply and demand shocks are identified using a combination of sign and zero restrictions, and estimate the model using Bayesian methods.

We mainly find that credit demand shocks are as important as credit supply shocks for economic fluctuations in the UK. A one standard deviation exogenous positive loan demand shock that moves both the credit demand and the lending rate variables in the same direction, leads to an increase in GDP of approximately 0.10% on impact and persistent over the first 3 to 4 quarters. Similarly, a one standard deviation exogenous positive loan supply shock that

⁴A key exception is Bassett et al. (2014) which we refer to in the literature review below.

 $^{{}^{5}}$ It is now well understood that monetary policy shocks affect GDP and prices through both credit supply and demand, thanks to the so-called theory of the credit channel of monetary policy. See Ciccarelli et al. (2015) and references therein for more details.

simultaneously moves credit supply and bank lending rate in opposite directions also results in an impact GDP response of about 0.10%, persisting over 3 to 4 quarters, as for the loan demand shock. Furthermore, the two shocks account for between 9 and 10% of the variance of GDP growth each. Hence, these findings are suggestive evidence that credit demand shocks also matter for output growth as do credit supply shocks, and should therefore not be overlooked by researchers or policy makers. Our result is robust to the inclusion of additional variables intended to control for endogeneity issues, to the use of proxy credit variables, to the assignment of arbitrary weights to the different types of loans, and to the use of alternative identification assumptions, among others. In addition, we also find that the UK economy is mostly driven by the mortgage loans market when analysing the effects of credit demand and supply shocks on GDP growth and inflation in a heterogeneous loan-types setting that includes business, mortgage and consumer loans.

Existing Literature

To our best knowledge, in the literature that uses VAR models to analyse the effects of credit shocks, this paper is the first attempt to formally investigate the relative importance of loan demand shocks versus loan supply shocks for economic fluctuations. Most of the existing studies have exclusively focused on the effects of credit supply shocks, considering as previously mentioned, that credit demand shocks are economically non-significant enough to be analysed, or pointing at identification challenges or data availability on the demand side of the credit market. Recent such studies include Gilchrist and Zakrajšek (2012), Gambetti and Musso (2017), Jimenéz et al. (2012), Peek et al. (2003), and Hristov et al. (2012), among many others.

Other studies that only identify credit supply shocks have tried to get around the endogeneity issues by purging the credit supply variable of bank-specific and/or macroeconomic factors (e.g. bank risk tolerance, general economic outlook) that potentially also affect the demand for credit. Works in this direction include Bassett et al. (2014) and Barnett and Thomas (2014). In particular, while Bassett et al. (2014) construct a credit supply indicator which is not contaminated by bank-specific and macroeconomic factors that can also affect the demand for credit, Barnett and Thomas (2014) instead try to control for demand factors in their model's setting. These studies differ from ours since they do not evaluate the relative importance of credit demand shocks versus credit supply shocks for the economy as we do, but rather focus on the analysis of the effects of "cleaner" loan supply shocks for the economy.

Finally, a closer account to our work, which also combines survey and macroeconomic data is Ciccarelli et al. (2015) that uses US and Euro Area data.⁶ Their aim is to test the theory of the credit channel of monetary policy by analysing the respective importance of credit supply and demand channels for GDP and prices in an economy subject to an exogenous monetary policy shock. Unlike them, we are primarily interested in analysing these channels through exogenous loan supply and demand shocks, using a combination of sign and timing restrictions to separately identify our credit and demand shocks, whereas Ciccarelli et al. (2015) only use timing restrictions in identifying their monetary policy shock.

The rest of the paper is organized as follows. Section 3.2 presents the data and describes the variables used in the analysis, including how we construct our credit supply and demand variables. Section 3.3 presents the model's specification, explain our identification strategy in more details, and comprehensively outline the estimation steps. Section 3.4 discusses our main result and some of several robustness tests that we conducted as part of a sensitivity analysis. This section also includes the additional result where we account for loan heterogeneity. Finally, section 3.5 summarizes our findings and proposes directions for further investigations.

3.2 Variables' Constructions and Data Sources

3.2.1 The Bank of England Credit Conditions Survey

I start by a concise presentation of the Bank of England Credit Conditions Survey, drawing from Driver (2007), before proceeding with the description of the credit and macroeconomic variables used in the analysis.

The Bank of England Credit Conditions Survey (CCS hereafter) is a quarterly survey intended to cover all lending activities to UK households and firms, conducted by lenders in the UK.⁷ It started in the second quarter of 2007, and consists of three sets of questionnaires that cover the lending activities of UK banks, building societies and other (non-bank) specialist lenders, in three distinct credit markets: secured loans to households, unsecured loans to households, and corporate loans. Each of these three questionnaires has its own sample, based on lenders' market shares in each market. Lenders with a market share of 1% or more in any market for two

 $^{^{6}}$ To conduct their analyses, Ciccarelli et al. (2015) use data from the Bank Lending Survey (BLS) conducted by the European Central Bank (ECB) for the Euro area, and the Senior Loan Officer Opinion Survey (SLOOS) on bank lending practices organized by the Federal Reserve Bank (FRB) for the US.

⁷The questionnaires, data, and guide for the survey can be found at http://www.bankofengland.co.uk/publications/Pages/other/monetary/creditconditions.aspx

consecutive quarters, are invited to complete the corresponding questionnaire(s). Once they are included, lenders continue to be surveyed until their market share drops below 0.8%.

Between 10 and 15 lenders typically complete each of the three questionnaires, with around 30 lenders being involved in the survey, which corresponds to a covering of between 75% and 85% of the lending in each credit market. This is substantially higher than the market coverage of the ECB's Bank Lending Survey (40%) and the Fed's Senior Loan Officer Opinion Survey (60%). Besides, while these other surveys are only backward looking, each question in the CCS also has a forward-looking element. Finally, the CCS includes details on some markets that the other surveys typically don't cover.

The CCS questions are related to changes in credit trends over the past three months relative to the previous three months, and the expectations about the changes over the next three months relative to the latest three months, hence-by allowing to capture forward-looking behaviours in credit market as mentioned earlier. The survey includes two groups of questions: common questions and specific questions. Common questions to all three questionnaires ask about changes in loan demand and supply, including the factors that are perceived to have been driving these movements. Besides, as the interest rates that lenders require on their loans may under- or overstate the true price of credit due to fees and other non-price terms, each questionnaire also asks about how both price and non-price terms are changing.

For instance, non-price terms include questions on maximum loan-to-value and loan-to-income ratios for the secured lending questionnaire, questions on credit card limits and minimum monthly repayments for the unsecured lending questionnaire, and questions on collateral requirements and loan covenants for the corporate lending questionnaire. Moreover, because lending terms and conditions can be affected by the magnitude of eventual losses that lenders may experience on their existing loans, each questionnaire asks about the proportion of loans that are in default. However, as this information is not enough to analyse the impact of defaults on lenders' balance sheets, the questionnaires also ask about losses given default.

Specific questions include the use of credit scoring by lenders when processing households credit applications. For a given set of characteristics, changing credit scoring criteria will affect the degree to which borrowers have access to credit. As a result, the secured and unsecured lending questionnaires also ask questions about how both credit scoring criteria and approval rates are changing over time. Besides, specific questions are also directed to particular markets. For example, the corporate lending questionnaire asks questions about demand and terms on lending to non-financial firms by size, as well as to other financial institutions. Finally, the secured and corporate lending questionnaires ask about lenders' use of tools such as securitization.

Respondents provide qualitative answers to the different questions about the changes in credit conditions, choosing from a series of five options ranging from 'up a lot' to 'down a lot'.⁸ These answers are then converted into scores that are assigned to each of the lenders based on their responses: lenders reporting that credit conditions have changed 'a lot' are assigned twice the score of those who report that conditions have changed 'a little'. Next, the scores are weighted by the lenders market shares and aggregated to produce quantitative net percentage balances. A net percentage balance is defined as the difference between the weighted balance of lenders reporting that lending conditions were higher (i.e., 'up a lot' and 'up a little'), and those reporting that lending conditions were lower (i.e., 'down a little' and 'down a lot').

Net percentage balances are scaled to lie between -100 and +100. Positive net percentage balances indicate that on average, lenders reported (or expected) demand (or credit availability) to be higher than the previous (or current) three-month period; or that the terms and conditions on which credit was approved became cheaper or looser respectively. For example, a positive net percentage balance in response to a question on loan demand means that lenders on average had experienced an increase in the demand for credit, while a negative net percentage balance in response to a question on credit scoring criteria would mean that lenders on average have tightened access to credit.

3.2.2 Credit Variables

We use the responses from the CCS in order to construct our credit supply and demand variables. These survey data are greatly suitable for our analysis for the following reasons:

(1) First, the survey allows to make inferences on the entire pool of potential borrowers and not only those who are actually granted loans, so that the data are not subject to sample bias.

(2) Second, the collected information is reliable as the survey is conducted by the Bank of England which also acts as the supervisory authority that can cross-check the banks' answers with supervisory data.

⁸These five options are precisely 'up a lot', 'up a little', 'unchanged', 'down a little', 'down a lot'.

(3) Third, the use of market shares as weighting coefficients in the computation of the net percentage balances confers a more accurate quantitative dimension to the data compared with arbitrary weights used in other similar surveys.

For the purpose of this study, we only focus on few questions from the CCS that we describe in Appendix A.1. In particular, we identify credit demand in the data using the answers on changes in loan demand that has been addressed to the lenders. Given this identification, we construct our credit demand variable by averaging over the changes in business, mortgage, and consumer loan demands, each of which is weighted by its respective share computed using seasonally adjusted and deflated sterling lendings data from the BoE Money and Credit Statistics.⁹

The loan supply variable is constructed in a similar way, except that its identification is now based on changes in credit availability from the lenders. Credit availability is defined as the ability and willingness of banks to provide credit to borrowers.

Finally, for the equilibrium interest rate, we construct a composite rate based on the end-ofperiod average bank lending rate for business, mortgage, and consumer loans, using data from the BoE Money and Credit Statistics. This composite lending rate proxies for the average price of credit, and is used in conjunction with the previously constructed credit variables, to uniquely identify credit supply and demand shocks.



FIGURE 3.1: Changes in Loan Supply and Demand over time

Note: This figure shows our constructed aggregate loan supply and demand variables time series.

FIGURE 3.1 above shows our constructed loan supply and demand variables time series. As one can notice, both series are weakly correlated (Correlation Coefficient = 0.3877). This weak

⁹We deflate these lending volume data using the GDP deflator before computing the weights.

correlation between loan supply and demand variables implies that they are presumably driven by different shocks that can be separated from each other.

3.2.3 Macroeconomic Variables

We use standard macroeconomic variables from the monetary VAR literature together with the previously defined credit variables. These macroeconomic variables include aggregate output, prices, and the monetary policy rate.

Aggregate output or real GDP is the seasonally adjusted chained volume measure of GDP that we directly retrieved from the Office for National Statistics (ONS), whereas prices are the seasonally adjusted implied GDP deflator index also from the ONS.

Finally, we use the BoE end quarter level of Gilt repo interest rate as our proxy variable to control for the stance of monetary policy.¹⁰ A more suitable choice for the policy rate would be the Bank official Rate, but this rate is subject to little variability over our sample period because the zero lower bound was hit.

All these data are seasonally adjusted at quarterly frequency. In addition, real GDP and prices have been made stationary by conversion into (log-percentage) growth rates, which also makes them consistent with the credit and the policy rate data, and for estimating a VAR in difference or growth.

3.3 Methodology

3.3.1 Model Specification

We include both the credit and the macroeconomic variables in a vector auto-regressive (VAR) model which consists of a system of regression equations where each variable depends on its own lags as well as the lags of all the other variables in the model, up to some pre-specified maximum lag order, p. The general unrestricted VAR(p) can be written in reduced-form as:

$$y_t = C + A_1 y_{t-1} + \dots + A_p y_{t-p} + \epsilon_t \tag{3.1}$$

 $^{^{10}{\}rm This}$ measure of stance is not a measure of exogenous shocks, but of policy actions. In other words, it is endogenous with respect to the state of the macroeconomy.

where y_t is a *n*-dimensional vector of endogenous variables, that is the $n \times 1$ vector of observed time series data at each time point t = 1, ..., T with T being the sample size, $\epsilon_t \sim N(0, \Sigma)$ an $n \times 1$ vector of zero mean white noise process, p the lag length, and $C, A_1, ..., A_p$ and Σ are matrices of suitable dimensions containing the model's unknown parameters. In particular, C is a $n \times 1$ vector of constant terms, $A_i, i = 1, ..., p$ is a $n \times n$ matrix of auto-regressive coefficients, whereas $\Sigma = E(\epsilon_t \epsilon_t')$ is the $n \times n$ covariance matrix of the residuals vector ϵ_t . These residuals are the reduced-form errors of the VAR, i.e., the linearly unpredictable component of y_t , given an information set consisting of the lagged values of all the model's variables. They have no underlying economic interpretation without further assumptions.

The reduced-form VAR(p) in Equation (3.1) can be thought of as representing data generated from the following structural VAR(p) model:

$$B_0 y_t = c + B_1 y_{t-1} + \dots + B_p y_{t-p} + \omega_t \tag{3.2}$$

where $c, B_1, ..., B_p$ are analogously defined as before, whereas the $n \times n$ invertible matrix B_0 reflects the instantaneous relations among the model's variables, and the $n \times 1$ vector of mean zero structural shocks ω_t is serially uncorrelated, with a diagonal covariance matrix Σ_{ω} of full rank, and such that the number of shocks coincides with the number of variables.^{11,12} The model in equation (3.2) is structural in the sense that the elements of ω_t are mutually uncorrelated, and have clear interpretations in terms of an underlying economic model. This allows to interpret movements in the data caused by any element of ω_t as being caused by that shock. The structural shocks can be recovered from the VAR reduced-form representation of equation (3.1) once this one has been derived by pre-multiplying both sides of equation (3.2) by B_0^{-1} , resulting in:

$$y_t = B_0^{-1}c + B_0^{-1}B_1y_{t-1} + \dots + B_0^{-1}B_py_{t-p} + B_0^{-1}\omega_t$$
(3.3)

where $C = B_0^{-1}c$, $A_i = B_0^{-1}B_i$, i = 1, ..., p, and $\epsilon_t = B_0^{-1}\omega_t$. The $n \times n$ structural impact multiplier matrix B_0^{-1} captures the impact effects of each of the structural shocks on each of the model's variables. Without loss of generality and as is standard with these settings, we normalize the covariance matrix of the structural errors $\Sigma_{\omega} \equiv E(\omega_t \omega_t') = I_n$ such that the reduced-form

 $^{^{11}}$ This rules out the possibility that the model includes equations that are merely identities, rather than being subject to stochastic errors.

 $^{1^{2}}$ This rules out the possibility for the data to be generated by economic models in which there are fewer than n structural shocks, such as the standard real business cycle model in which all macroeconomic aggregates are only driven by a technology shock such that the covariance structure of the data is singular.

errors covariance matrix is obtained as

$$E(\epsilon_t \epsilon_t') = \Sigma = E(B_0^{-1} \omega_t \omega_t' B_0^{-1'}) = B_0^{-1} E(\omega_t \omega_t') B_0^{-1'} = B_0^{-1} B_0^{-1'} = (B_0' B_0)^{-1}.$$

One can think of $\Sigma = (B_0'B_0)^{-1}$ as a system of n(n+1)/2 non-linear independent equations in the unknown parameters of B_0^{-1} .¹³ Solving for this latter system requires the imposition of additional identifying restrictions on the elements of B_0^{-1} , that can be motivated by economic theory and/or timing assumptions. Given these restrictions and the data, the structural shocks $\omega_t = B_0 \epsilon_t$ are said to be identified, and the reduced-form errors ϵ_t can be decomposed into the mutually uncorrelated structural shocks ω_t . However, it is worth stressing that it is not enough for the elements of ω_t to be mutually uncorrelated for the model in equation (3.2) to be structural, one also needs a clear economic interpretation of these elements. In other words, one should note that even if all the elements of ω_t are uniquely identified in a statistical sense, they need not be uniquely identified in the economic sense. The problem of finding suitable economically credible restrictions on B_0^{-1} or its inverse B_0 is known as the identification problem in structural VAR analysis.

Identification Strategy 3.3.2

Our benchmark model for the analysis of the effects of credit supply and demand shocks includes seven variables: real GDP growth, inflation, the credit supply and demand variables, the lending rate, the growth rate of the nominal GDP-to-loans ratio, and the policy rate.¹⁴

As we are primarily interested in identifying credit demand and supply shocks only, we adopt a partial identification strategy in the spirit of Bernanke and Blinder (1992) and Arias et al. (2019). Besides, since each of these two credit shocks implies a different set of restrictions, we can disentangle them by applying each set of restrictions to the corresponding column of the impact multiplier matrix as discussed in the previous section. For that, we impose a combination of signs and zeros restrictions based on economic theory and timing assumptions.

For the signs restrictions in particular, we follow economic theory and the micro-founded DSGE literature as best illustrated in Gambetti and Musso (2017) which surveys a set of

¹³Due to the symmetry of Σ , there are only n(n+1)/2 independent equations in n(n+1)/2 unknown parameters

of B_0^{-1} . ¹⁴We show in a sensitivity analysis not reported but available on request, that using GDP and prices levels in lieu of growth rates does not affect our main result.

benchmark structural macroeconomic models with structural shocks that can be associated with loan supply disturbances, and reports that the vast majority of them find that a credit supply shock moves loan supply and the lending rate in opposite directions. Moreover, these structural DSGE models imply that a positive credit supply shock that increases loan volume on impact would also lead to an increase in GDP, inflation and the policy rate.¹⁵ As for loan demand shocks, we assume, following economic theory and the impulse responses implied by core structural DSGE models from the debt (de-)leveraging literature, that a credit demand shock simultaneously moves loan demand and interest rate in the same direction, both comoving with GDP, inflation, and the policy rate as illustrated in Table 1 below. In particular, these benchmark structural models that include Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2017), Justiniano et al. (2015b), Justiniano et al. (2019), and Philippon and Midrigan (2011), consider disturbances in the form of exogenous changes in debt limits or LTVs that can be linked to credit demand shocks.

TABLE 3.1 :	Impulse	Responses	to a	Negative	Credit	Demand	Shock i	in Struct	ural	Debt
Deleveraging DSGE Models.										

Model	Shock Nature	Output Growth	Inflation	Policy Rate	Borrowing Volume	Borrowing Rate
Eggertsson and Krug- man (2012)	Fall in exogenous debt limit	\downarrow	\downarrow	Ļ	Ļ	\downarrow
Guerrierri and Loren- zoni (2017)	Fall in exogenous borrowing limit	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow
Justiano et al. (2015, 2019)	Fall in maximum LTV	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow
Midrigan and Philippon (2011)	Fall in both LTV and Housing Prefer- ence	Ļ	\downarrow	Ļ	\downarrow	\downarrow

Note: Macroeconomic effects of a negative loan demand shock in structural DSGE models featuring debt (de-)leveraging. A negative loan demand shock implies changes with the same sign for output growth, inflation, the policy rate, credit volume and the borrowing rate. Whereas the credit demand shock that moves loan quantity and the interest rate in the same direction is associated with exogenous changes in borrowing limits or LTVs in Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2017), Justiniano et al. (2015b) and Justiniano et al. (2019), Philippon and Midrigan (2011) rather consider disturbances in the form of simultaneous changes in LTVs and consumers' preferences for housing to allow their model to match aggregate data.

Intuitively, knowing that credit supply and demand shocks move loan quantities in the same direction and their prices in opposite directions helps to differentiate shifts due to credit demand shocks from those due to credit supply shocks. The ideas underlying these signs restrictions are as follows. In the event of an exogenous positive credit supply shock through which banks decide to expand the supply of loans to firms and households, they typically do so by increasing the

¹⁵In particular, Gambetti and Musso (2017) derives the loan supply shock sign restrictions from Christiano et al. (2010), Gertler and Karadi (2011), Gerali et al. (2010), and Curdia and Woodford (2010). In addition to Gambetti and Musso (2017), other empirical analyses that derive credit supply shocks signs restrictions from baseline structural DSGE models include Barnett and Thomas (2014), Hristov et al. (2012), Eickmeier and Ng (2015), and Duchi and Elbourne (2016), among others.

volume of loans available and/or by decreasing the lending rate so that both effects are observed at the aggregate level. This would lead to an increase in output as households borrow more to expand consumption whereas enterprises also do so to increase investment. The increased consumption and investment expenditure would then put an upward pressure on prices resulting in higher inflation. As for credit demand, a positive loan demand shock triggered for instance by an exogenous disturbance stemming from rising asset prices, would increase the value of borrowers' collaterals and induce them to take on more debts, putting upward pressure on borrowing rates by the law of supply and demand. Then, similar to the credit supply shock case, more borrowings would increase consumption and investment and therefore aggregate demand, resulting in higher price levels.

Besides, the impact responses of the benchmark's five other structural shocks are left agnostic in line with the partial identification scheme. These disturbances include aggregate supply and demand shocks, monetary policy shock, and other residual shocks. However, because our identified loan demand shock can be confused with an aggregate demand shock which may imply the same impact sign responses, we need to find a way to distinguish between these two shocks. For that, we borrow an intuitive and plausible assumption from Gambetti and Musso (2017) according to which a loan demand shock leads to a decrease in the nominal GDP-to-Loans ratio whereas aggregate demand shocks (e.g., preference shocks, investment shocks, etc.) would have the opposite effect on this ratio.

The intuition behind this idea is that a positive loan demand shock that leads to an increase in loans' quantity and the lending rate (as would an aggregate demand shock), would imply an increase in the amount of loans higher than the increase in nominal GDP, as long as the full amount of the additional granted loans is not spent but partly saved for precautionary reasons or speculative purposes for example. ¹⁶ The higher volume of loans compared to the increase in nominal GDP in turn implies a decrease in the GDP-to-Loans ratio. However, a positive aggregate demand shock, to the extent that the additional consumption or investment expenditure is not fully financed by new loans but through savings or retained earnings for instance, would lead to an expansion in nominal GDP higher than the increase in bank loans volume, thereby implying an increase in the GDP-to-Loans ratio, as illustrated in TABLE 3.2 below.

Turning now to the zero restrictions, we use the following timing assumption. We suppose that credit market disturbances affect the credit and macro variables on impact and the policy rate with a lag. This timing restriction amounts to the assumption that the Central Bank adjusts

 $^{^{16}}$ If the total amount of the additional granted loans was spent, this shock would qualify more correctly as an aggregate demand shock.

its policy rate only after observing the effects of the credit shock on GDP and prices. Besides, this delayed reaction also ensures that the stance of the monetary policy does not influence the effects of the credit shock on the economy at least on impact. Finally, together with the partial identification scheme, the zero restriction of only the policy rate to the credit shocks ensures that our identification approach is robust to a wide range of SVAR models. Yet the set of structural parameters satisfying these restrictions could be large and potentially include parameters with questionable implications that might substantially impact inference. This concern of Kilian and Murphy (2012) is also expressed in Arias et al. (2019). Because our identification strategy is not immune to this remark, we ran a battery of sensitivity tests using various specifications and found our main result to be robust to each of these specifications.

TABLE 3.2 below displays the summary of the signs and zeros restrictions for the baseline model. The signs in the table denote the impact responses of the baseline variables to both credit shocks, whereas the ? symbol denotes an agnostic response of the GDP-to-Loans ratio to a credit supply shock on impact. Finally, the zeros mean that the policy rate reacts with a lag to the credit shocks.

Variables	Credit Supply Shock	Credit Demand Shock
Loan Supply	+	+
Loan Demand	+	+
Lending Rate	—	+
Output Growth	+	+
Inflation	+	+
GDP-to-Loans Ratio	?	—
Policy Rate	0	0

TABLE 3.2: Summary of the Baseline Model Signs and Zeros Restrictions.

Note: The signs $(+ \text{ or } \ge 0, \text{ and } - \text{ or } \le 0)$ denote the impact responses of the baseline variables to both credit shocks, the ? symbol denotes an agnostic response of the GDP-to-Loans ratio to a credit supply shock on impact, and the zeros mean that the policy rate reacts with a lag to the credit shocks.

Illustration of Credit Demand Shocks Signs Restrictions

I now present a graphical illustration in partial equilibrium of how exogenous credit demand shocks lead to a co-movement of loan quantities and prices, both in the case where agents' borrowing constraints bind and don't bind. Even though this simple illustration is based on the "Ceteris Paribus" assumption, it however serves as a validation exercise for the identifying sign restrictions of the credit demand shocks, including the scenario where the equilibrium is at the debt limit where the borrowing constraint binds (see FIGURE 3.3 below).



FIGURE 3.2: Illustration of Loan Demand Shocks in Standard Credit Markets

Note: This figure illustrates the scenario of standard credit markets in a neoclassical setting with no credit frictions and where borrowing constraints are always slack.

In particular, FIGURE 3.2 below shows the case corresponding to the standard credit market in a neoclassical setting with no credit frictions and where borrowing constraints are always slack. As can be seen from the graph, a credit demand shock in the form of an exogenous disturbance that affects the borrowing capacity of borrowers, inducing them to lever up or de-lever, leads to upward or downward shifts of the loan demand curve CD_0 along the loan supply curve CS_0 , resulting in new equilibria characterised by the co-movement of credit quantity and price.

Interestingly, this co-movement of loan volume and interest rate also holds when borrowing constraints bind and agents borrow up to their debt limits as illustrated in FIGURE 3.3 below. In particular, an adverse credit demand shock shifts the credit demand schedule to the left from CD_0 to CD_1 , resulting in a new equilibrium at point A_1 , with both a lower interest rate and lower debt level. Intuitively, this negative loan demand shock induces a fall in the demand for debt, which generates an excess supply of debt, all things else being equal. The interest rate therefore needs to drop in order to re-establish the equilibrium in the credit market. A similar mechanism is at play in the event of a positive loan demand shock, which would shift the credit demand curve to the right along the credit supply curve, resulting in a new equilibrium at A_2 with higher debt and interest rate.



FIGURE 3.3: Illustration of Credit demand Shocks when Borrowing Constraints Bind

Note: This figure illustrates the scenario where credit markets are subject to financial frictions, and therefore borrowers are constrained by the amount of loans they can obtain from lenders. These borrowing constraints can take the form of exogenously fixed debt limits or collateral constraints.

3.3.3 Estimation

After imposing the sign and zero restrictions, we estimate the model using the algorithm proposed by Arias et al. (2018) in a Bayesian setting. This algorithm makes independent draws from a family of conjugate posterior distributions over the structural parametrization conditional on the sign and zero restrictions. More precisely, it draws from a conjugate posterior distribution over the orthogonal reduced-form parametrization and then transforms the draws into the structural parametrization.

Detailed description of the algorithm steps can be found in Appendix A.3, but let us comprehensively summarize it here:

(i) Basically, as is common in the Bayesian VAR (BVAR henceforth) literature, Arias et al. (2018) use the normal-inverse-Wishart density as their choice of the family of conjugate distributions over the reduced-form parametrization, and a uniform conjugate density over the set of orthogonal matrices conditional on the reduced form parameters.
(ii) Then, independent draws from the Uniform-Normal-Inverse-Wishart posterior distribution satisfying both the sign and zero restrictions are simulated using an Importance Sampler.

(iii) Next, thanks to a change of variable theory developped by the authors, these draws are mapped into the structural parametrization and, finally used for inferences.¹⁷

The BVAR estimation approach is not only suitable for our small sample size, but interestingly also deals with the large number of parameters to be estimated. It does so by incorporating prior information about these unknown parameters in order to produce an estimated model that is not as highly sensitive to the particular data set used for the estimation.

For the choice of the prior distribution, we follow Giannone et al. (2015) and combine three key priors commonly used in the literature, that are the Minnesota priors, the sum-of-coefficients priors, and the dummy-initial-observation priors. This helps to reduce estimation uncertainty by shrinking the densily parameterized unrestricted VAR of Equation (1.1) towards a parsimonious model, resulting in a more accurate estimation of impulse response functions.

The prior is then formally combined with the information contained in the data as captured by the likelihood function of the model, to estimate the posterior probability distribution from which the earlier described draws are made. Details of the BVAR estimation's steps along with Arias et al. (2018)'s theory and simulation techniques are extensively exposed in Appendix A.2.

3.4 Results

3.4.1 Main Result

3.4.1.1 Impulse Response Functions

We start by comparing the IRFs of the effects of credit demand and supply shocks for output growth and inflation in this baseline model.

As illustrated in FIGURE 3.4.(a) below, a one standard deviation exogenous positive loan demand shock that increases both credit demand and the lending rate, leads to an increase in loan supply by banks of about 2% on impact, whereas output increases by just above 0.10% on impact, and persists over the first three to four quarters. Comparatively, FIGURE 3.4.(b) shows

 $^{^{17}{\}rm This}$ theory shows that a Uniform-Normal-Inverse-Wishart density over the orthogonal reduced-form parametrization implies a Normal-Generalized-Normal density over the structural parametrization.



FIGURE 3.4: Impulse responses for the Baseline model



(a) Credit Demand Shock

(b) Credit Supply Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

that a one standard deviation exogenous positive loan supply shock that simultaneously increases credit supply and decreases the lending rate, increases demand of credit by approximately 4% on impact, but more importantly results in GDP rising by about 0.10% and persistent over the next four quarters as for the positive loan demand shock. This short-lasting effect of our credit supply shock on real GDP growth is qualitatively in line with the one obtained by Gambetti and Musso (2017) following an expansionary loan supply shock.

In particular, our finding suggests that credit demand and supply disturbances are broadly both equally important in explaining output fluctuations. Therefore the widespread belief that credit supply shocks are more important for economic fluctuations and that credit demand shocks have only marginal and non-significant effects on the economy, seems misleading. Finally, on can notice that the effects of both credit shocks on inflation are positive on impact as on should expect, triggering an upward adjustment of the policy rate by the central bank.

3.4.1.2 Forecast Error Variance Decomposition

To corroborate our previous result, we now report the contributions of the credit shocks to the forecast error variances (FEVs) of the different endogenous variables of the model, where our interest is in checking whether both credit shocks have contributed equivalently to output fluctuations. For ease of exposition, we only show the contributions to the FEVs at horizons 4, 12, and 20 for selected endogenous variables including output growth.¹⁸

As can be seen from TABLE 3.3 below, the share of real GDP growth FEV attributable to each of the two shocks is above 9%, at each horizon, which reinforces our previous conclusion that both credit demand and supply shocks have similar quantitative effects on output fluctuations.

	4th Quarter		12th Quarter		20th Quarter	
Variables	Credit Supply Shock	Credit Demand Shock	Credit Supply Shock	Credit Demand Shock	Credit Supply Shock	Credit Demand Shock
Loan Supply	0.1051	0.0815	0.1151	0.0888	0.1143	0.2160
	[0.0358, 0.2308]	[0.0284, 0.1853]	[0.0411, 0.2199]	[0.0330, 0.1909]	[0.0426, 0.2160]	[0.0322, 0.1945]
Loan Demand	0.1652	0.2190	0.1569	0.2040	0.1560	0.2020
	[0.0722, 0.3326]	[0.0890, 0.4357]	[0.0745, 0.3056]	[0.0906, 0.4054]	[0.0744, 0.3061]	[0.0923, 0.4040]
GDP	0.0996	0.0937	0.0972	0.0906	0.0970	0.0935
	[0.0296, 0.2540]	[0.0227, 0.2309]	[0.0336, 0.2435]	[0.0249, 0.2125]	[0.0332, 0.2391]	[0.0253, 0.2145]
Inflation	0.1003	0.0695	0.1011	0.0722	0.1017	0.0750
	[0.0196, 0.3030]	[0.0178, 0.2129]	[0.0207, 0.2963]	[0.0219, 0.2081]	[0.0214, 0.2950]	[0.0219, 0.2084]

TABLE 3.3: Shares of FEVD attributable to credit shocks for selected variables

Note: The columns report for each variable, the posterior median and the 68% equally tailed probability intervals of the FEVD attributable to credit shocks at different horizons. The table is based on more than 1,000 independent importance sampling draws obtained using Arias et al. (2018)'s algorithm.

 $^{^{18}{\}rm The}$ main result that both credit shocks contribute in a similar way to GDP variations holds at the other horizons as well.

3.4.2 Robustness Analysis

In this section, we conduct a series of robustness tests to check the sensitivity of our main finding to various alternative specifications.

Use of Alternative Weightings for the Different Loan Types

Our first robustness test consists in using arbitrary weightings of the shares of the different types of loans in the credit market. In particular, the use of equal weights does not affect the main finding that both credit demand and supply shocks have similar effects on output fluctuations, as illustrated in FIGURE 3.5 below.

Additional Control Variables

As a second robustness test, we are interested in testing whether our credit supply and demand shocks are truly exogenous. If they are, there should be no need to control for additional variables intended to address potential endogeneity issues. For that, we extend the benchmarch model with three new control variables that are the bank-specific factors, the borrower-specific factors, and the general economic outlook (i.e., changes in the outlook for output, income, employment, and inflation).

The bank-specific factors variable is constructed by averaging over different potential lendingrelated factors (such as market share objectives, competition pressure, and risk appetite) of the changes in credit supply. Similarly, the borrower-specific factors variable is obtained by averaging over different possible borrowing-related factors (e.g., capital investment, inventory finance, and balance sheet restructuring) of the changes in credit demand.

As already mentioned above, the inclusion of these three additional control variables are intended to address potential endogeneity issues which may arise from aggregate supply and/or demand shocks, among others. For instance, changes in the general economic outlook which obviously affect both lending and borrowing activities, may also influence consumption and investment decisions by households and firms, which in turn feed back to loan growth. Meanwhile, changes in bank-specific and borrower-specific factors which primarily affect credit supply and demand respectively, may also affect the other side of the credit market. Importantly, these later changes are crucial to control for possible endogenous changes in both banks' credit policies and borrowers' demand for loans, respectively.



FIGURE 3.5: Impulse responses for the model with alternative weightings

(a) Credit Demand Shock

Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

As can be seen from FIGURE 3.6 below, our main result is also robust to this extended 10-variable VAR specification, hence-by suggesting robustness to both the inclusion of additional control variables and the size of the VAR. The credit shocks therefore appear to be truly exogenous.





⁽a) Credit Demand Shock

Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

Proxy Credit Variables

In this third robustness test, guided by economic theory, we combine loans volume's growth rate with the lending rate to specify the credit shocks as in the baseline, that is the credit supply shock moving the lending volume and rate in opposite directions whereas the credit demand shock moves them in the same direction.¹⁹ Interestingly, as FIGURE 3.7 below illustrates, this alternative 6-variable VAR specification of the model with the loan volume's growth rate does not also affect our main conclusion.

FIGURE 3.7: Impulse responses for the model with loans volume's growth rate



(a) Credit Demand Shock

Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

¹⁹In this exercise, we are identifying both credit shocks using loan quantities and prices, as opposed to the identification involving the credit supply and demand variables that we constructed from the survey.

Use of Alternative Priors

We also estimate the baseline model using non-informative priors, i.e., priors with minimal impact on the posterior distribution of the parameters. A common choice for non-informative prior is the flat prior which assigns equal likelihood on all possible values of the parameters, as opposed to Giannone et al. (2015)'s informative prior that we use in the baseline model.

FIGURE 3.8: Impulse responses for the model with flat priors

(a) Credit Demand Shock



(b) Credit Supply Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

FIGURE 3.8 above shows the impulse response functions (IRFs) for which we made use of flat priors. As can be noticed, the main result is unaffected by the use of these flat priors.

Alternative Timing Assumption

An alternative timing identifying restriction commonly used in the credit shocks VAR literature is to assume that the credit shock affects the credit variables on impact, and the macroeconomic variables (including the policy rate) with a lag.

FIGURE 3.9: Impulse responses for the model with an alternative timing assumption

(a) Credit Demand Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

The intuition behind this assumption is that credit shocks typically take some time to propagate to the real economy. For example, a contraction in credit supply does not affect firms' production in the current period, but rather in the subsequent one(s) through restricted investment possibilities due to lower funds availability. As can be seen from FIGURE 3.9 above, our baseline finding is qualitatively unaffected by this alternative timing assumption.

Identifying an Additional Shock

In this final exercise, in addition to our shocks of interest (i.e., credit demand and supply shocks), we also identify an aggregate demand shock to meaningfully distinguish it from the credit demand shock. As in TABLE 3.2, the signs in TABLE 3.4 below denote the impact responses of the variables to the credit and aggregate demand shocks, whereas the ? symbol denotes an agnostic response of the GDP-to-Loans ratio to a credit supply shock on impact, and the zeros mean that the policy rate reacts with a lag to the credit and aggregate demand shocks.

 TABLE 3.4: Summary of the Signs and Zeros Restrictions in the Model with three Identified Shocks.

Variables	Credit Supply Shock	Credit Demand Shock	Aggregate Demand Shock
Loan Supply	+	+	+
Loan Demand	+	+	+
Lending Rate	—	+	+
Output Growth	+	+	+
Inflation	+	+	+
GDP-to-Loans Ratio	?	_	+
Policy Rate	0	0	0

Note: The signs $(+ \text{ or } \ge 0, \text{ and } - \text{ or } \le 0)$ denote the impact responses of the variables to the credit and aggregate demand shocks, the ? symbol denotes an agnostic response of the GDP-to-Loans ratio to a credit supply shock on impact, and the zeros mean that the policy rate reacts with a lag to the credit and aggregate demand shocks.

As one can notice from the FIGURE 3.10 below, our main result is also robust to identifying the aggregate demand shock in addition to our two credit shocks of interest. In particular, simulating the model with a higher number of draws consistently leads to a smaller impact difference on output growth for both credit shocks, comforting our conclusion that both shocks have similar quantitative effects on GDP growth.

3.4.3 Heterogeneous Loan-Types Credit Transmission Channels

This additional analysis attempts to determine which of the three types of loans - business, mortgage and consumer - mostly drive(s) UK's economy. In other words, we are interested in determining in this heterogenous loan-types economy, through which type(s) of loan, credit supply and demand shocks mostly affect the economy. For that, we specify a new model that

FIGURE 3.10: Impulse responses for the Model with three Identified Shocks



(a) Credit Demand Shock

Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

includes credit supply and demand by loan type, GDP, prices, and the policy rate. In addition, we also include in the model the baseline credit supply and demand variables as well as the corresponding average lending rate, to identify aggregate credit shocks as in the proxy credit variables robustness exercise. Hence, the imposition of joint signs and zeros restrictions are reminiscent of the identification strategy used in the baseline framework, with the exception that this time we identify one credit shock at a time.

From FIGURE 3.10 below, one can see that a credit demand shock in panel (a) affects GDP and prices through a much stronger effect on the mortgage loans market, i.e., both supply and demand sides with an increase of about 3% and 5% on impact, respectively. Meanwhile, the transmission channel is rather modest through the non-financial business loans market (slightly above 1.5% impact responses for both supply and demand of business loans), presumably owing to the fact that firms usually have access to alternative funding sources or rely on their retained earnings.

In addition, credit supply shocks (Panel (b)) also affect output growth and inflation mostly through the mortgage loans market, with the supply of mortgage loans increasing by above 2.5% on impact against 2% and 1.5% for the supply of consumer and business loans respectively, whereas the demand for mortgage loans is just below 5% on impact against only 1.5% and 2% for the demand for business and consumer loans respectively. These stronger effects of credit supply shocks through the mortgage loans market are in line with the observation that the UK mortgage loans market is directly affected by supply-side policies such as borrowing restrictions by lenders. Besides, the fact that credit demand shocks also affect output growth and inflation primarily through the mortgage loans market may be an indication that the UK mortgage loans market is also affected by demand-side policies.

All together, these two findings suggest that the UK economy is significantly driven by variations in mortgage credit.



FIGURE 3.11: Impulse responses for the model with heterogeneous loan-types

(a) Credit Demand Shock

Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

3.5 Conclusion

Overall, the evaluation of the relative importance of credit demand and supply shocks for the UK economy suggests that both disturbances are equally important for output fluctuations. This result is obtained by combining the Bank of England Credit Conditions Survey data with standard monetary macroeconomic variables in a VAR identified by signs and zeros restrictions and estimated using Bayesian techniques along the lines of Arias et al. (2018). It is robust to several alternative specifications, including the extension of the model with additional control variables, the use of alternative definitions for the credit variables, the estimation of the model with flat priors, the assignment of arbitrary weights to the different types of loans, and the use of alternative identifying restrictions. This appealing finding based on reliable survey data, sharply contrasts with the common belief that credit demand shocks have marginal effects on the economy and should therefore not retain policy makers' attention.

Another interesting result, that the UK economy is significantly driven by the mortgage loans market, is obtained by considering the effects of credit shocks on the economy in a heterogeneous loan-types setting that includes business, mortgage and consumer loans.

These findings have important policy implications. Credit demand shocks being important for the economy implies that policy makers should undertake actions that directly influence loan demand, in addition to already implemented supply-side policies. This could be done through an accommodating monetary policy that ought to lower borrowing rates or increase access to credit, thereby encouraging households and firms to take on more loans for consumption and investment expenditures. Besides, since the UK economy is significantly driven by the mortgage loans market, the BoE could design and implement policies that help strengthen both supply and demand of mortgage loans.

Further investigations of the relative importance of credit demand and supply shocks for economic fluctuations, could use other identification strategies as the proxy SVAR approach best illustrated by Mertens and Ravn (2013) and Stock and Watson (2012), where one could construct proxy credit variables using narrative accounts, which would then be used as instruments to estimate loan demand and supply shocks.

Chapter 4

Credit Demand Shocks and the Business Cycle

In light of the previous chapter's robust VAR evidence that credit demand shocks are important for economic fluctuations, this paper aims at analysing their transmission channels to the economy. To provide a structural interpretation for the empirical result and shed light on the transmission mechanisms of credit demand shocks to the real economy, I propose a financial frictions DSGE framework featuring borrowing households and firms as well as a banking sector. The model simulations suggest that credit demand shocks propagate to the economy through both a Fisher deflation and a collateral channel. In addition, the model predicts that when borrowing constraints are allowed to bind occasionally, credit demand shocks are more persistent and lead to higher amplification effects on the economy through the combined effects of the Fisher deflation and collateral channels.^{1,2}

¹I am heavily indebted to Michael Hatcher for many insightful comments and feedbacks on this paper. I am also grateful to Alessandro Mennuni, Chiara Forlati and Serhiy Stepanchuk for useful comments and feedbacks. ²The paper also benefited from comments and suggestions from conference participants at the 2018 RES PhD Meetings in London, the 2019 RES annual conference at the University of Warwick, the 2019 Catalan Economic Society Conference (CESC) in Barcelona, and the contributed sessions of the 34th congress of the European Economic Association at the University of Manchester.

Introduction 4.1

Since the wake of the 2008 financial crisis, there has been a surge in the studies that analyse the effects of credit markets frictions for economic fluctuations. Whereas the great majority of these works has focused on understanding the transmission mechanisms of credit supply shocks to the economy, the analysis of the importance of loan demand shocks for the business cycle and the channels through which they propagate to the real economy have received less attention.³

Therefore, my main objective is to assess the importance of credit demand shocks for business cycle fluctuations by shedding light on the transmission channels of exogenous loan demand shocks to the real economy. It is worth stressing that the focus of this chapter is to analyse the implications of exogenous loan demand shocks for the business cycle in general, and not the boom-bust cycle associated with the developments that led to the recent Great Recession. In particular, in light of the previous chapter's VAR evidence that credit demand shocks are important for economic fluctuations and given the scant investigation of their transmission channels, I propose a financial frictions DSGE model featuring borrowing households and firms as well as a banking sector, that will help to provide a structural interpretation of how these loan demand shocks propagate to the real economy. The structural framework will thus allow to analyse the channels through which an exogenous shock stemming from a fall in borrowings from households and firms, affects output, consumption, and investment.

For that, I modify the framework by Gerali et al. (2010) to accommodate loan demand shocks.⁴ In particular, I assume that a credit demand shock occurs as an exogenous disturbance stemming for example from booming or busting house prices, expected lower or higher returns on investment or more generally pessimism or optimism about the future economic outlook.⁵ This exogenous shock simultaneously affects both borrowers, inducing them to lever up or de-lever, which translates in an upward or downward shift in their loan demand curves, respectively, in line with the identifying sign restrictions of the loan demand shock in the VAR model.

Among competing shocks used in the DSGE literature, including preference shocks, housing demand shocks, and different variants of LTV shocks, cumulative LTV (i.e., the total outstanding debt-to-value ratios) shocks are the ones that can account for the VAR impulse responses to

 $^{^{3}}$ In particular, credit supply shocks constitute the great bulk of the disturbances introduced in the financial frictions models, in the form of tighter or looser credit conditions.

⁴Gerali et al. (2010) analyse the role of loan supply factors for economic fluctuations by estimating a mediumscale financial frictions DSGE model embedding a monopolistic competitive banking sector with sticky interest rates. They find, among other results, that a credit supply shock in the form of an unexpected destruction of bank capital may have substantial effects on the business cycle. ⁵Credit demand shocks thus arise from voluntary (de)-leveraging as opposed to forced deleveraging following a

credit crunch as in Guerrieri and Lorenzoni (2017), or debt overhang as in Maffezzoli and Monacelli (2015).

credit demand shocks.⁶ None of the other candidate shocks matches the VAR sign restrictions. In particular, I show in section 4.3.3 below that they all lead to different responses of most variables in the model, compared with those of the cumulative LTV shock. Instead, this later shock is qualitatively in line with the responses of the VAR variables to the loan demand shock, closely matching the co-movement of loans quantities and prices, but also the opposite movement of the GDP-to-loans ratio which ensures that the credit demand shock is not confused with an aggregate demand shock.

The model simulations suggest that credit demand shocks propagate to the economy both through a Fisher deflation and a collateral channel. In particular, an exogenous negative loan demand shock that hits the economy around the steady-state where the borrowing constraints always bind, leads to a decrease in both the borrowing rates and the amount of loans requested by households and firms. The decrease in the demand for loans in turn leads to households and firms reducing consumption and investment, which depresses aggregate demand through a decrease in output, resulting in lower prices and therefore lower values for the assets used as collateral. The deflationary pressure increases the real burden of debt through the Fisher deflation channel. This higher outstanding real debt combined with the lower collateral values, will contract further agents demand for loans in the subsequent period, resulting in an even lower aggregate demand, and so on. The opposite is true in the event of a positive loan demand shock. In addition, the model predicts that when borrowing constraints are allowed to bind occasionally, credit demand shocks are more persistent and lead to higher amplification effects on the economy through the combined effects of the Fisher deflation and collateral channels.

Literature

While this paper investigates the transmission channels of credit demand shocks to the real economy, most of the existing literature that embeds financial frictions in DSGE models focuses on the mechanisms through which loan supply shocks propagate to the economy. These credit supply shocks generally stem from the supply side of credit, through banks and other financial intermediaries expanding or restricting access to credit for various reasons including their balancesheets' strength, their risk appetite, regulatory capital requirements, or borrowers perceived riskiness, among others.

⁶I highlighted in section 2.4.2 of chapter 2 above how LTV shocks could be interpreted either as credit demand or supply shocks; yet only a specific type of these shocks closely matches the VAR model identifying sign restrictions to a credit demand shock.

Examples of models with credit supply shocks include Jermann and Quadrini (2012) and Christiano et al. (2014) that highlight borrowing constraints faced by non-financial firms. Another group of loan supply shocks models is tied to the strand of the credit frictions literature that incorporates balance-sheet constraints on banks or embeds shocks stemming from financial intermediaries' behaviour (such as risk appetite). This latter literature includes Curdia and Woodford (2010), Gerali et al. (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gambacorta and Signoretti (2014), and Cúrdia and Woodford (2016) among others. In all these models, credit supply shocks propagate to the economy through the financial accelerator mechanism.

Finally, closely related to credit demand shocks is the growing debt deleveraging literature inspired by the recent developments linked to the Great Recession, and where balance-sheet constrained households are forced to de-lever by adjusting downwards their consumption expenditures following an unexpected reduction in their borrowing capacity. This recent literature includes Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2017), and Justiniano et al. (2015b), among others.

The rest of the paper is organized as follows. Section 4.2 describes the construction of the model in more details, and section 4.3 presents simulations results of credit demand shocks experiments and how they differ from other shocks. Finally, section 4.4 concludes.

4.2 Model

In Chapter 3, I provided robust evidence that credit demand shocks are important for economic fluctuations in a VAR setting. Yet, while the mechanisms through which credit supply shocks transmit to the economy have been extensively investigated, little is known about how credit demand shocks propagate to the real economy. Therefore, in this section, I construct a full structural DSGE model featuring borrowers and lenders, to analyse the transmission channels of credit demand shocks to the economy.

For that, I borrow some features from Gerali et al. (2010) that analyse the role of credit factors for business cycle fluctuations by estimating a medium-scale financial frictions DSGE model embedding a monopolistic competitive banking sector with sticky interest rates.⁷ In particular, I share with Gerali et al. (2010) the main characteristics of the financial sector. First,

⁷For details on theoretical and empirical arguments in favor of the imperfect competitive banking sector and the stickiness of the interest rates, the reader can refer to the first section of Gerali et al. (2010).

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a borrower balance-sheet channel modelled along the lines of Kiyotaki and Moore (1997) by assuming that households or firms' borrowing capacity is linked to the value of the assets that they can pledge as collateral. Second, a bank lending channel stemming from the presence of a target level for banks' leverage, which target can be thought of as an exogenous constraint imposed by regulatory authorities. The framework thus features constraints on both borrowers and lenders that allows for shifts in credit demand and supply curves, respectively. In addition, the presence of a banking sector in the model allows to clearly account for the supply-side of credit so that the general equilibrium analysis of the effects of credit demand shocks is conducted while explicitly taking into account the reaction of credit providers.

Besides, Gerali et al. (2010) focus on credit supply shocks in the form of either interest rate spreads shocks on loans to firms and households, or shocks to bank capital occurring as an unexpected destruction of bank equity. Instead, I consider a credit demand shock defined as an exogenous disturbance that simultaneously affects the borrowing capacity of all borrowers (households and firms alike), inducing them to request more or less credit, which implies movements in the lending rates in the same direction through upward or downward shifts in the loan demand curve. For instance, a positive credit demand shock can be thought of as triggered by optimism about the general economic outlook, including expectations of higher returns on future investment opportunities, that pushes both borrowers to lever up, whereas a negative loan demand shock could be assimilated to a pessimism shock (e.g., fears around the Brexit, etc.) that would induce both borrowers to de-lever.

A candidate shock that is in line with the identifying assumptions of the loan demand shock in the VAR model and qualitatively matches its impulse responses, is the cumulative LTV shock that affects all borrowers simultaneously. None of the other competing shocks used in the DSGE literature lead to impulse responses in line with those produced by the VAR model to credit demand shocks. In particular, I show in section 4.3.3 below that a standard LTV shock to either households or firms, a housing demand shock or a preference shock all lead to different responses of most variables in the model compared to those of the cumulative LTV shock.

The Economy

The economy is populated by savers that are the patient households (p), and borrowers that are the impatient households (i) and the entrepreneurs (e), each type having unit mass. Households consume, work, and accumulate housing (in fixed supply), while entrepreneurs produce a homogeneous intermediate good using capital produced in a decentralised sector, and labor from households. The three types of agents differ by their degree of impatience: the discount factor of patient households (β_p) is higher than those of impatient households (β_i) and entrepreneurs (β_e) .

Besides, I modify the financial sector in Gerali et al. (2010) to make it simpler and more tractable yet keeping its key features. In particular, as in Gambacorta and Signoretti (2014), I assume that banks are perfectly competitive in the deposit market and set the interest rate on deposits equal to the policy rate, and monopolistically competitive in the loan market: they charge a constant mark-up on the spread between the lending and deposit rates. Hence, banks obtain funding from patient households' savings collection, and also accumulate capital out of reinvested earnings. They issue loans that are financed through the collected deposits and their own capital, to both impatient households and entrepreneurs, and modify lending margins (i.e., tightening or loosening of loan supply conditions) in order to attain an exogenously fixed level of capital-to-assets ratio that is the target level of bank leverage mentioned previously. The loan margins will thus depend on the banks' actual capital-to-assets ratio and also on the degree of interest rate stickiness. Loans issued to impatient households and entrepreneurs are collateralised by their stocks of housing and capital, respectively, in the spirit of Kiyotaki and Moore (1997)'s limited commitment.

Moreover, as is standard in New Keynesian settings, I assume that a monopolistic competitive retail sector buys intermediate goods from entrepreneurs in a competitive market, brand them at no cost and sell the differentiated goods at a price which includes a mark-up over the purchasing cost. Prices are sticky à la Rotemberg (1982), implying the existence of a New Keynesian Phillips curve. In addition, in order to derive an explicit expression for the market price of capital, I introduce capital goods producers and assume that new capital creation is subject to adjustment costs. Finally, monetary policy is conducted according to a Taylor type rule.

4.2.1 Savers: Patient Households

Patient household i solves the following problem:

$$\max_{\{c_{p,t}(i), l_{p,t}(i), h_{t}(i), d_{p,t}(i)\}} E_0 \sum_{t=0}^{\infty} \beta_p^t \Big[(1-a_p) log(c_{p,t}(i) - a_p C_{t-1}) + \varphi log(h_{p,t}(i)) - \frac{l_{p,t}(i)^{1+\phi}}{1+\phi} \Big]$$

which depends on its individual consumption $c_{p,t}$ and lagged aggregate consumption C_{t-1} , housing $h_{p,t}$ and hours $l_{p,t}$. The parameter a_p measures external consumption habits, and $(1-a_p)$ is a scaling factor that ensures that the marginal utility of consumption is independent of habits in the non-stochastic steady state. Finally, φ is the weight of housing in the utility function, and ϕ is labour dis-utility parameter.

Besides, the patient household's optimal choices are subject to the following flow of budget constraint:

$$c_{p,t}(i) + q_{h,t}(h_{p,t}(i) - h_{p,t-1}(i)) + d_{p,t}(i) \le w_{p,t}l_{p,t}(i) + \frac{(1+r_{d,t-1})}{\pi_t}d_{p,t-1}(i) + J_{R,t}(i)$$
(4.1)

where expenses include the patient household's current consumption, its accumulation of housing which real price is $q_{h,t}$, and its current bank deposits $d_{p,t}$. Resources consist of labor earnings $w_{p,t}l_{p,t}$, $w_{p,t}$ being the real wage rate, gross interest income on last period deposits $\frac{(1+r_{d,t-1})}{\pi_t}d_{p,t-1}$ where $\pi_t \equiv \frac{P_t}{P_{t-1}}$ is gross inflation, and real profits $J_{R,t}$ from retailers of which patient households are the only owners. The full set of the model's equations is provided in Appendix B.1.

4.2.2 Borrowers

4.2.2.1 Impatient Households

Impatient household i solves the following problem:

$$\max_{\{c_{i,t}(i), l_{i,t}(i), h_{i,t}(i), b_{i,t}(i)\}} E_0 \sum_{t=0}^{\infty} \beta_i^t \Big[(1-a_i) log(c_{i,t}(i) - a_i C_{t-1}) + \varphi log(h_{i,t}(i)) - \frac{l_{i,t}(i)^{1+\phi}}{1+\phi} \Big]$$

where $c_{i,t}$, C_{t-1} , $h_{i,t}$, $l_{i,t}$, a_i , ϕ , and φ are analogously defined as before. The impatient household's decision problem is subject to the following budget constraint:

$$c_{i,t}(i) + q_{h,t}(h_{i,t}(i) - h_{i,t-1}(i)) + \frac{(1 + r_{bh,t-1})}{\pi_t} b_{i,t-1}(i) \le w_{i,t} l_{i,t}(i) + b_{i,t}(i)$$
(4.2)

where the flow of expenses includes the impatient household's current consumption $c_{i,t}$, its accumulation of housing $q_{h,t}(h_{i,t} - h_{i,t-1})$, and gross reimbursement of borrowing $\frac{(1+r_{bh,t-1})}{\pi_t}b_{i,t-1}$, whereas its resources consist of labor income $w_{i,t}l_{i,t}$ and new loans $b_{i,t}$.

In addition, the impatient household faces the following borrowing constraint:

$$(1 + r_{bh,t})b_{i,t}(i) \le m_{i,t}E_t[q_{h,t+1}\pi_{t+1}h_{i,t}(i)]$$
(4.3)

Equation (4.3) states that the household's current (gross) debt cannot exceed a fraction $m_{i,t}$ of the expected future value of its house. In particular, I interpret variations in the loan-to-value parameter $m_{i,t}$ as credit demand shocks, i.e., exogenous changes in the form of booming or busting house prices that affect households' borrowing capacity and induce them to increase or decrease their demand for loans.⁸ In section 4.4 below, I show that loan demand shocks as identified in the VAR model, are closely matched by shocks to the cumulative LTVs (or outstanding debt-to-value) of all borrowers.

$$m_{i,t}$$
 is assumed to follow the following AR(1) process:
 $log(m_{i,t}) = (1 - \rho_{m_i})log(\overline{m}_i) + \rho_{m_i}log(m_{i,t-1}) + \epsilon_{m_i,t}$
(4.4)

where \overline{m}_i is its steady-state value, ρ_{m_i} the persistence parameter, and $\epsilon_{m_i,t} \sim \text{ i.i.d } N(0, \sigma_{m_I}^2)$.

4.2.2.2 Entrepreneurs

Entrepreneur i solves the following problem:

$$\max_{\{c_{e,t}(i), l_{pe,t}(i), l_{ie,t}(i), b_{e,t}(i)\}} E_0 \sum_{t=0}^{\infty} \beta_e^t \Big[(1 - a_e) log(c_{e,t}(i) - a_e C_{t-1}) \Big]$$

subject to the flow of budget constraint

$$c_{e,t}(i) + w_{p,t}l_{pe,t}(i) + w_{i,t}l_{ie,t}(i) + \frac{(1+r_{be,t-1})}{\pi_t}b_{e,t-1}(i) + q_{k,t}k_{e,t}(i) \le \frac{y_{e,t}(i)}{x_t} + b_{e,t}(i) + q_{k,t}(1-\delta_k)k_{e,t-1}(i)$$

$$(4.5)$$

in which resources spent for consumption $c_{e,t}$, labor inputs $l_{pe,t}$ and $l_{ie,t}$, gross reimbursement of borrowing $\frac{(1+r_{be,t-1})}{\pi_t}b_{e,t-1}$, and new capital $q_{k,t}(k_{e,t}-(1-\delta_k)k_{e,t-1})$, have to be financed with income from the sale of a wholesale good $y_{e,t}$ and new loans $b_{e,t}$. In addition, δ_k is the capital depreciation rate, and x_t the mark-up of the retail sector with $\frac{1}{x_t} \equiv \frac{P_{W,t}}{P_t}$ being the relative price of the wholesale good produced using the technology

$$y_{e,t}(i) = A_t k_{e,t-1}(i)^{\alpha} l_{e,t}(i)^{1-\alpha}$$
(4.6)

where A_t is the TFP shock and follows the following stochastic process:

$$log(A_t) = (1 - \rho_A)log(\overline{A}) + \rho_A log(A_{t-1}) + \epsilon_{A,t}$$

$$(4.7)$$

with $\epsilon_{A,t} \sim \text{ i.i.d } N(0, \sigma_A^2)$, \overline{A} the steady-state value, and ρ_A the persistence parameter.

Besides, labor $l_{e,t}$ combines inputs from patient and impatient households according to $l_{e,t} = (l_{pe,t})^{\psi}(l_{ie,t})^{1-\psi}$, where ψ measures the labor income share of patient households.

Entrepreneurs obtain funding from banks subject to the following borrowing constraint: $(1 + r_{be,t})b_{e,t}(i) \le m_{e,t}E_t[q_{k,t+1}\pi_{t+1}(1 - \delta_k)k_{e,t}(i)]$ (4.8)

⁸As already mentioned previously, depending on the underlying analysis, these LTV shocks can also be interpreted as credit supply shocks based on borrowers perceived riskiness by lenders, as in most collateral constraints frameworks where these loan supply shocks propagate to the economy through the financial accelerator mechanism.

where $m_{e,t}$ is analogously defined as in the household's case, and given by the following AR(1) process:

$$log(m_{e,t}) = (1 - \rho_{m_e})log(\overline{m}_e) + \rho_{m_e}log(m_{e,t-1}) + \epsilon_{m_e,t}$$

$$(4.9)$$

with $\epsilon_{m_e,t} \sim \text{ i.i.d } N(0, \sigma_{m_e}^2)$, \overline{m}_e the steady-state value, and ρ_{m_e} the persistence parameter.

4.2.3 Banking Sector

As in Gerali et al. (2010), I assume that each bank in the economy is composed of a retail branch in charge of providing differentiated loans to impatient households and entrepreneurs in a monopolistic competitive manner, and a perfectly competitive wholesale unit that manages the bank's capital position.

Each wholesale unit j collects deposits $d_{b,t}(j)$ from patient households on which it pays the policy rate r_t , and issues wholesale loans $b_t(j)$ on which it earns the wholesale loan rate $r_{b,t}$. Moreover, the bank has own funds $k_{b,t}(j)$ which are accumulated out of reinvested profits as follows:

$$\pi_t k_{b,t}(j) = (1 - \delta_b) k_{b,t-1}(j) + j_{b,t-1}(j)$$

where δ_b is the fraction of the bank's capital that is used each period in banking activity, and $j_{b,t}$ are overall profits generated by the two units of the bank. In addition, the bank pays a quadratic cost whenever its capital-to-assets ratio $k_{b,t}(j)/b_t(j)$ deviates from a given leverage target ν that can be interpreted either as an exogenously fixed constraint stemming from regulatory measures, or as capturing the trade-offs that would arise in the decision regarding the amount of own resources to hold.

More precisely, the wholesale branch optimally chooses loans and deposits that solve the following problem:

$$\max_{\{b_t(j),d_{b,t}(j)\}} E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^p \Big[(1+r_{b,t})b_t(j) - \pi_{t+1}b_{t+1}(j) + \pi_{t+1}d_{b,t+1}(j) - (1+r_t)d_{b,t}(j) \\ + (\pi_{t+1}k_{b,t+1}(j) - k_{b,t}(j)) - \frac{\kappa_{k_b}}{2} \Big(\frac{k_{b,t}(j)}{b_t(j)} - \nu \Big)^2 k_{b,t}(j) \Big]$$

subject to balance-sheet constraint $b_t(j) = d_{b,t}(j) + k_{b,t}(j)$, and taking $r_{b,t}$ and r_t as given. Besides, because banks are owned by patient households, they value future profits using the discount factor $\Lambda_{0,t}^p$. After some algebraic manipulations where the balance-sheet constraint is used twice, the wholesale bank's problem boils down to:

$$\max_{\{b_t(j), d_{b,t}(j)\}} r_{b,t} b_t(j) - r_t d_{b,t}(j) - \frac{\kappa_{k_b}}{2} \left(\frac{k_{b,t}(j)}{b_t(j)} - \nu\right)^2 k_{b,t}(j)$$

The first order condition results in:

$$S_{W,t} \equiv r_{b,t} - r_t = -\kappa_{kb} \left(\frac{k_{b,t}(j)}{b_t(j)} - \nu \right) \left(\frac{k_{b,t}(j)}{b_t(j)} \right)^2$$
(4.10)

implying that in equilibrium, the bank chooses a level of loans that equalizes the marginal benefit (i.e., the increase in profits equal to the spread $S_{W,t}$), and the marginal cost which is the increase in the costs of deviating from ν .

The retail loan branch of bank j buys loans from the wholesale unit at rate $r_{b,t}$, differentiates them at no cost and resells them to final borrowers, that are households and firms, applying a constant additive markup μ_b on the wholesale rate.⁹ The retail loan rates for both borrowers are thus given by:

$$r_{bH,t} = r_{bE,t} = r_t - \kappa_{k_b} \left(\frac{k_{b,t}(j)}{b_t(j)} - \nu\right) \left(\frac{k_{b,t}(j)}{b_t(j)}\right)^2 + \mu_b = r_{b,t} + \mu_b \tag{4.11}$$

Finally, bank j overall profit $j_{b,t}(j)$ is the sum of net earnings from the two branches:

$$j_{b,t}(j) = r_{bH,t}b_{H,t}(j) + r_{bE,t}b_{E,t}(j) - r_t d_{b,t}(j) - \frac{\kappa_{k_b}}{2} \left(\frac{k_{b,t}(j)}{b_t(j)} - \nu\right)^2 k_{b,t}(j)$$
(4.12)

where $b_t(j) = b_{H,t}(j) + b_{E,t}(j)$.

4.2.4 Capital Goods Producers

Perfectly competitive capital goods producers purchase undepreciated capital from entrepreneurs and final goods from retailers, and combine them to produce new capital or investment goods I_t , subject to adjustment costs. They solve the following problem:

$$\max_{\{I_t\}} E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^e \left(q_{k,t} \left[1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t - I_t \right) \right)$$

The first order condition with respect to I_t results in:

⁹Different from Gerali et al. (2010) where the monopolistic competition markup in the loan market is multiplicative, time-varying and different for each borrower, I assume, for the sake of simplicity and in line with Gambacorta and Signoretti (2014), that the markups for both borrowers are identical, constant and additive. This choice does not affect the cyclical properties of banks profits.

$$1 = q_{k,t} \left[1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 - \kappa_I \left(\frac{I_t}{I_{t-1}} - 1 \right) \left(\frac{I_t}{I_{t-1}} \right) \right] + \beta_e E_t \left[\frac{\lambda_{e,t+1}}{\lambda_{e,t}} q_{k,t+1} \kappa_I \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right]$$
(4.13)

In the aggregate, capital is accumulated according to the following law of motion:

$$K_t = (1 - \delta_k) K_{t-1} + \left[1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t$$
(4.14)

where κ_I is the investment adjustment costs parameter.

4.2.5 Retailers

Monopolistically competitive firms produce the retail goods which prices are sticky and indexed to steady-state inflation π . If they want to deviate from the steady-state price, they face a quadratic adjustment cost as in Rotemberg (1982), parameterized by κ_P .

In more details, retailer j solves the following problem:

$$\max_{\{P_t(j)\}} E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^p \left[P_t(j) y_t(j) - P_{W,t} y_t(j) - \frac{\kappa_P}{2} \left(\frac{P_t(j)}{P_{t-1}(j)} - \pi \right)^2 P_t Y_t \right]$$

subject to the demand addressed to her and derived from consumers' maximization problem:

$$y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\varepsilon_y} Y_t \tag{4.15}$$

where ε_y is the demand price elasticity, $P_{W,t}$ and P_t the wholesale and retail goods prices, respectively.

In a symmetric equilibrium, the first order condition with respect to $P_t(j)$ results in the following New Keynesian Phillips curve:

$$\kappa_P(\pi_t - \pi)\pi_t + \varepsilon_y - \frac{\varepsilon_y}{x_t} - 1 = \beta_p E_t \left[\frac{\lambda_{p,t+1}}{\lambda_{p,t}} \kappa_P(\pi_{t+1} - \pi)\pi_{t+1} \frac{Y_{t+1}}{Y_t} \right]$$
(4.16)

4.2.6 Monetary Policy

The central bank sets its policy rate r_t according to a Taylor-type rule:

$$(1+r_t) = (1+r)^{(1-\phi_r)} (1+r_{t-1})^{\phi_r} \left(\frac{\pi_t}{\pi}\right)^{\phi_\pi (1-\phi_r)} \left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y (1-\phi_r)} (1+\varepsilon_{r,t})$$
(4.17)

where ϕ_{π} and ϕ_{y} are weights assigned to inflation and output stabilization, respectively, r is the steady-state policy rate, π the steady state inflation is also the inflation target, and $\varepsilon_{r,t}$ is a white noise monetary policy shock with standard deviation σ_{r} .

4.2.7 Equilibrium and Definitions of Aggregate Variables

The model is closed by the equilibrium conditions in the goods, credit, housing and labor markets.

The market clearing condition in the goods market is:

$$Y_t = C_t + [K_t - (1 - \delta_k)K_{t-1}]$$
(4.18)

where $Y_t = \gamma_e y_t$ is aggregate output, $C_t = \gamma_p c_{p,t} + \gamma_i c_{i,t} + \gamma_e c_{e,t}$ is aggregate consumption, $K_t = \gamma_e k_{e,t}$ is the aggregate stock of physical capital, and γ_a , $(a \in \{p, i, e, b\})$, is the share of agent *a*, i.e., the measure of each subset of agents, and is normalized to 1.

The market clearing conditions in the labor and the housing markets are, respectively, given by:

$$\gamma_e l_{pe,t} = \gamma_p l_{p,t} \tag{4.19}$$

$$\gamma_e l_{ie,t} = \gamma_i l_{i,t} \tag{4.20}$$

and

$$\overline{h} = h_{p,t} + h_{i,t} \tag{4.21}$$

where \overline{h} is the housing stock, in fixed supply.

The equilibrium condition in the credit market is:

$$B_t = D_t + K_{B,t} \tag{4.22}$$

that is the aggregate bank balance-sheet identity, where $B_t = B_{h,t} + B_{e,t}$ is the economy's aggregate loans with $B_{h,t} = \gamma_b b_{H,t}$ and $B_{e,t} = \gamma_b b_{E,t}$. $D_t = \gamma_p d_{p,t} = \gamma_b d_{b,t}$ is aggregate deposits, and $K_{B,t} = \gamma_b k_{b,t}$ is the aggregate bank capital.

Finally, aggregate bank profits $J_{B,t}$ is defined as $J_{B,t} = \gamma_b j_{b,t}$.

4.3 Loan Demand Shock Experiments

In order to analyse the channels through which credit demand shocks propagate to the economy, I design two experiments. In the first one, I solve the model using standard log-linearisation techniques, approximating the equations around the non-stochastic steady-state. In the second exercise, I use a perfect foresight algorithm to account for some non-linearities inherent to these types of models, namely the possibility that the borrowing constraints may only bind occasionally, which cannot be accommodated using the log-linearisation method.

I assume that a credit demand shock is triggered by an exogenous disturbance stemming for example from expected lower or higher returns on investment or more generally pessimism or optimism about the future economic outlook. This exogenous shock simultaneously hits households and firms alike, inducing both borrowers to lever up or de-lever. In order to replicate the identifying sign restrictions of the credit demand shock in the VAR framework, I try different candidates shocks commonly used in similar settings, and find that shocks that hit the cumulative LTV ratios of both borrowers alike are the ones that match the VAR impulse responses to credit demand shocks. To allow for these shocks to hit both borrowers simultaneously, I assume that the white noise components $\epsilon_{m_e,t}$ and $\epsilon_{m_i,t}$ of households and entrepreneurs cumulative LTVs, respectively, are identically distributed, and denote this distribution as $\epsilon_{m,t}$, with $\epsilon_{m,t} \sim i.i.d N(0, \sigma_m^2)$.¹⁰

Besides, this credit demand shock is different from an exogenous change in collateral requirements by the lenders, or associated with looser lending constraints due to credit markets liberalisation as spelled out in Justiniano et al. (2015a). These two disturbances better qualify as loan supply shocks. Moreover, I show in section 4.4.2 below that the other candidate shocks in the literature result in different responses of the macroeconomic and financial variables than those generated by the cumulative LTV shock which are in line with the VAR-identified credit demand shock IRFs.

4.3.1 Calibration

The calibration is summarised in TABLE 4.1 below and is based on U.S. aggregate data. The parameters have been calibrated to target key steady-states that are extensively derived in Appendix B.2. The unit of time is a quarter. I set the steady-state gross inflation π to 1.005, implying that the central bank is targeting a 2% annual inflation rate, in line with the Fed's medium term target. The patient households' discount factor β_p is set to 0.993 in order to match the historical long term average Effective Federal Funds Rate of 4.83% (annualised). As for the borrowers' subjective discount factors β_i and β_e , I set them to 0.965 and 0.955, respectively, close to commonly used values in the literature. The patient households' labor income share ψ is calibrated at 0.8, which is consistent with the one estimated in Iacoviello and Neri (2010). The weight of housing in households' utility function, φ , is set at 0.2 to match a real estate-to-GDP

 $^{^{10}}$ This is also in line with the credit demand shock of the VAR framework which is applied to the aggregate of households (through mortgage and consumer) and firms (through business) loans along with the corresponding average interest rate. The construction of these two later variables are explained in section 3.2.2 of the previous chapter.

ratio of 1.15 computed from the Flow of Funds Accounts and NIPA data as the average ratio between the market value of real estate of households and nonprofit organisations and GDP, both de-trended by the HP filter. The inverse of the Frisch elasticity ϕ is set to 1 (Galí (2015)). This value is an average between the one derived from linear utility and the low elasticities of labor supply usually estimated in the micro-econometric literature.

Capital's share in the production function, α , and its depreciation rate δ_k are set to 0.20 and 0.05, respectively, as in Gambacorta and Signoretti (2014). The investment adjustment cost κ_I is calibrated at 10.18 as estimated by Gerali et al. (2010). The elasticity of substitution across goods, ε_y , is set at 6, implying a gross mark-up in the goods market of 1.20, a value commonly used in the literature. Consistent with the evidence in Nakamura and Steinsson (2008), I set the degree of price stickiness κ_p at 28.65. Given ε_y , this corresponds to a Calvo probability of 66% of not being able to adjust prices, which implies that retailers are able to adjust their prices every 3 quarters on average. The degree of monetary policy inertia ϕ_r , its reaction to the output gap ϕ_y and to inflation ϕ_{π} are set to 0.77, 0.35 and 2.0, respectively, close to their estimated values in Gerali et al. (2010), and are in line with available empirical estimates of the Taylor rule in the post-1984 period.

The credit market's parameters are calibrated to replicate key business cycles statistics of the banking sector. I first set the steady-state DTV ratio m_e of entrepreneurs to 0.54, the US non-financial firms average historical cumulative LTV ratio. As for the one of the households, m_i , I set it to 0.85 in line with the cumulative LTV ratio adjusted for first time home buyers estimated by Duca et al. (2011). The target capital-to-asset ratio ν is set at 8%, the minimum capital adequacy ratio that banks must maintain under Basel III. I set the cost for managing the bank capital position δ_b at 0.059 as in Gambacorta and Signoretti (2014). The bank capital adjustment cost κ_{k_b} is set to 11.07, the estimated median value in Gerali et al. (2010). Finally, I set the steady-state value of the loan spread at 2% annualized, implying a constant markup over the lending rate charged by the retail bank of $\mu_b = 0.5\%$.

4.3.2 Log-linearisation

In a steady-state perturbation experiment where the model is solved using log-linearisation, I assume that a negative credit demand shock adversely affects the borrowing capacity of households and firms alike through a simultaneous decrease in their cumulative LTVs, inducing them to reduce their demand for loans. FIGURE 4.3 below presents the responses of the main financial

Parameter	Description	Value	Source/Target
π	Gross inflation	1.005	The Fed's medium term target
β_p	Patient households' discount factor	0.993	Average Fed Funds rate of 4.83% (annualized)
β_i	Impatient households' discount factor	0.965	Literature
β_e	Entrepreneurs' discount factor	0.955	Literature
ψ	Patient households' labor income share	0.8	Iacoviello and Neri (2010)
φ	Housing weight in utility function	0.2	Real estate-to-GDP ratio of 1.15, from Z1 and NIPA
ϕ	Inverse of the Frisch elasticity	1	Gali (2015)
α	Capital's share in the production function	0.20	Gambarcota and Signoretti (2014)
δ_k	Capital depreciation rate	0.05	Gambarcota and Signoretti (2014)
κ_I	Investment adjustment cost	10.18	Gerali et al. (2010)
ε_y	Elasticity of substitution across goods	6	Literature
κ_p	Price stickiness	28.65	Nakamura and Steinsson (2008)
ϕ_r	Monetary policy inertia	0.77	Gerali et al. (2010)
ϕ_y	Monetary policy reaction to output gap	0.35	Gerali et al. (2010)
ϕ_{π}	Monetary policy reaction to inflation	2.0	Gerali et al. (2010)
m_i	Households' DTV ratio	0.85	Duca et al. (2011)
m_e	Entrepreneurs' DTV ratio of	0.54	Average cumulative LTV ratio, from Z1
ν	Target capital-to-asset ratio	0.08	Basel III
δ_b	Cost for managing bank capital position	0.059	Gambarcota and Signoretti (2014)
κ_{k_b}	Bank capital adjustment cost	11.07	Gerali et al. (2010)
μ_b	Markup over the lending rate	0.005	2% spread target (annualised)
$\gamma_j, j \in \{p, i, e, b\}$	Share of agents	1	Standard normalisation
$a_j, j \in \{p, i, e\}$	Habit coefficients	0.86	Gerali et al. (2010)

TABLE 4.1: Model Parameters' Calibration

Note: These parameters have been calibrated to target some key steady-state ratios which computations are detailed in Appendix B.2.

and macroeconomic variables to the credit demand shock. These results are not meant to be quantitatively rigorous since the main purpose of the paper is to shed light on the transmission channels of credit demand shocks to the economy.

At time zero, the economy is at its steady-state where the borrowing constraints bind for both impatient households and entrepreneurs. Then, the economy is perturbed by the exogenous negative loan demand shock that pushes both borrowers to reduce their demand for loans, resulting in lower interest rates. This lower credit demand is corroborated by a positive response of the output-to-loans ratio, in line with the credit demand shock identification of the VAR framework in section 3.3.2 of the previous chapter.¹¹ The decrease in the demand for loans will in turn lead to households and firms reducing consumption and investment, thus decreasing aggregate demand and prices. Then, these lower price levels will not only lead to a deflationary pressure that will increase the real burden of debt through the well known Fisher deflation channel, but will also decrease the values of the assets used as collateral, reducing the borrowing capacity of households and firms. Higher outstanding real debt and lower collateral values will contract further agents demand for loans in the subsequent period, depressing even further aggregate demand, and so on.

 $^{^{11}}$ In that section, I argue that this output-to-loans ratio can be used to distinguish a loan demand shock from an aggregate demand shock which would then result in a negative response of the output-to-loans ratio following the adverse shock.



FIGURE 4.3: Effects of an adverse shock to the cumulative LTVs of all borrowers around the Steady-State

Note: This figure reports the responses of financial and macroeconomic variables to an adverse shock to the cumulative LTVs of all borrowers, that is a negative loan demand shock, which qualitatively matches the impact sign responses of the VAR variables to a similar credit demand shock. These IRFs are obtained by solving the model by log-linearization and simulating it around the non-stochastic steady-state.

4.3.3 Credit Demand Shock versus Other Shocks

The previous experiment suggests that credit demand shocks propagate to the economy through both the Fisher deflation mechanism and a collateral channel, whereas credit supply shocks are known to affect the economy via different channels working through the so-called financial accelerator mechanism. Appendix B.3 provides an example of how credit supply shocks propagate to the economy, thereby illustrating the difference between their transmission mechanisms and those of a credit demand shock.

Besides, to show how other competing shocks commonly used in these macroeconomic settings fail to match the impulse responses to the VAR loan demand shock, I now plot the IRFs of the macroeconomic and financial variables to an adverse shock to households and entrepreneurs' LTVs, respectively, as well as to a housing demand shock. FIGURE 4.4 below illustrates the responses of the macroeconomic and financial variables to an adverse households' LTV shock. As one can notice, this negative LTV shock generates qualitatively different responses for loans to firms, investment and hours worked compared with their responses to an adverse loan demand shock of the same size from FIGURE 4.3 above. In particular, as FIGURE 4.4 shows, an adverse LTV shock reduces the borrowing capacity of households inducing them to reduce their demand

for loans, thus putting a downward pressure on interest rates. Importantly, these lower borrowing rates push firms to borrow more as credit becomes cheaper and use the additional funds to increase investment. In contrast, because the adverse credit demand shock simultaneously affects households and firms instead, it results in lower loan demand for both agents.



FIGURE 4.4: Effects of a Household LTV Shock around the Steady-State

Note: This figure reports the responses of financial and macroeconomic variables to a negative household LTV shock. These IRFs are obtained by solving the model by log-linearisation and simulating it around the non-stochastic steady-state.

Turning now to the effects of an adverse firm LTV shock illustrated in FIGURE 4.5 below, one can notice that all the variables respond in a qualitatively similar manner as for the adverse loan demand shock, a key exception being the output-to-loans ratio which different response suggests that the firm LTV shock does not qualify as a loan demand shock, owing to the arguments presented in section 3.3.2 of the previous chapter to distinguish a credit demand shock from an aggregate demand shock.

Finally, I also repeat the same exercise with a housing demand shock which leads to different responses for most of the variables, as illustrated in FIGURE 4.6 below.

All these perturbation exercises have provided good analytical insights about how credit demand shocks propagate to the economy in the neighbourhood of the steady state. However, solving a model using a log-linearised equilibrium system is well known to be a poor approximation of the underlying economy's non-linearities, particularly when borrowing constraints do not always bind. As a matter of fact, the perturbation approach used to simulate the model is only valid



FIGURE 4.5: Effects of a Firm LTV Shock around the Steady-State

Note: This figure reports the responses of financial and macroeconomic variables to a negative firm LTV shock. These IRFs are obtained by solving the model by log-linearization and simulating it around the non-stochastic steady-state.

FIGURE 4.6: Effects of a Housing Preference Shock



Note: This figure reports the responses of financial and macroeconomic variables to a negative housing preference shock.

around the steady state; as the economy moves away from it (e.g., following a large shock), not only the quality of the linear approximation deteriorates but also the conditions that ensure that the borrowing constraints bind in the steady state might not hold anymore. Therefore I now turn to solving the model using a perfect foresight algorithm that allows to account for the possibility that the borrowing constraints may bind only occasionally.

4.3.4 Occasionally Binding Constraints

I handle the possibility of occasionally binding borrowing constraints using the perfect foresight method of Adjemian et al. (2011), which is based on the work by Fair and Taylor (1983). This approach uses a relaxation Newton algorithm to solve the non-linear model over a finite time period horizon, and offers a better control over the accuracy of the solution.

At period zero, the economy is at its steady-state where the borrowing constraints bind as in the previous log-linearisation experiment. Then, the agents perfectly anticipate that there will be a transitory shock in period 1 and no other shocks thereafter (i.e., from period 2 onwards). I assume that this transitory disturbance is a positive loan demand shock that can be interpreted as optimism about the future economic outlook which induces households and firms to increase their demand for loans in period 1 after the shock has occurred.

FIGURE 4.6: Effects of an adverse shock to the cumulative LTVs of all borrowers with Occasionally Binding Constraints



Note: This figure reports the responses of financial and macroeconomic variables to an adverse shock to the cumulative LTVs of all borrowers, that is a negative loan demand shock, which qualitatively matches the impact sign responses of the VAR variables to a similar credit demand shock. These IRFs are obtained by solving the model using the perfect foresight approach that accounts for occasionally binding borrowing constraints.

As FIGURE 4.6 below illustrates, the positive loan demand shock leads to an increase in the amount of business and household loans, resulting in an upward movement in interest rates and a downward pressure on the output-to-loans ratio as one would expect from the VAR identifying assumptions. The increase in loan demand also leads to higher consumption and investment expenditures, thereby increasing aggregate demand that is met by the increase in output, resulting in higher prices and hours worked. The higher inflation then leads to a lower value for the real debt through a reverse Fisher deflation channel. This later Fisher effect, coupled with increased value of the collateralised assets (owing to the higher levels of prices), pushes households and firms to demand even more debt in the subsequent periods. Hence, as in FIGURE 4.3, credit demand shocks are propagated through both a Fisher deflation and a collateral channel.

Besides, unlike FIGURE 4.3 where the effects of the credit demand shock on the macroeconomic variables were short lived, they are long-lasting in this experiment instead, mostly because the setting now accommodates the occasionally binding borrowing constraints. By allowing for these occasionally binding borrowing constraints, one can notice that credit demand shocks are now more persistent and lead to higher amplification effects through the combined effects of the Fisher deflation and collateral channels.

As a robustness test, I also handle the possibility of occasionally binding borrowing constraints using the perfect foresight method with surprises, still based on Adjemian et al. (2011). Unlike the standard perfect foresight approach where the aftermath of the one-time shock is perfectly anticipated, the perfect foresight method with surprises instead assumes an unexpected sequence of shocks that cannot be anticipated by the agents. Hence, the use of a sequence of consecutive shocks is crucial to accommodate the perfect foresight algorithm with surprises.

More precisely, for simplicity, I use a sequence of two consecutive positive loan demand shocks in this experience, and assume that at period zero the economy is at its deterministic steady-state where the borrowing constraints bind. Then, the agents anticipate, as in the standard perfect foresight case, that there will be a transitory shock in period 1 and no other shock thereafter (i.e., from period 2 onwards). However, they are surprised in period 2 by another shock, which they did not anticipate. Then no other shock occurs afterwards until the economy returns back to its deterministic steady-state.

As FIGURE 4.7 below illustrates, the responses of the different variables to the positive credit demand shocks turn out to be qualitatively similar to those of the expected shock in FIGURE 4.6 above.



FIGURE 4.7: Effects of unexpected adverse shocks to the cumulative LTVs of all borrowers.

Note: This figure reports the responses of financial and macroeconomic variables to an adverse shock to the cumulative LTVs of all borrowers, that is a negative loan demand shock, which qualitatively matches the impact sign responses of the VAR variables to a similar credit demand shock. These IRFs are obtained by solving the model using the perfect foresight approach with surprises where the shocks cannot be anticipated by the agents

4.4 Conclusion

Overall, based on chapter 3 empirical evidence that credit demand shocks are important for economic fluctuations, this chapter sheds light on the transmission channels of these shocks to the real economy in a financial frictions DSGE model with occasionally binding borrowing constraints.

The model predicts that credit demand shocks propagate to the economy through both the Fisher deflation and collateral channels. Adverse loan demand shocks that perturb the economy in the neighbourhood of the steady-state where the borrowing constraints always bind, lead to lower aggregate demand through a decrease in consumption and investment expenditures, and lower prices which work to exacerbate the decrease in aggregate demand via both the Fisher deflation mechanism and a collateral channel. The opposite is true in the event of a positive loan demand shock. In addition, when borrowing constraints are allowed to bind occasionally, credit demand shocks are more persistent and lead to higher amplification effects on the economy through the combined effects of the Fisher deflation and collateral channels.

However, among plausible shocks from the DSGE literature, only a very specific type of credit market shocks, i.e., the cumulative LTV shock, is in line with the identifying restrictions
of the loan demand shock in the VAR model and matches the impact sign responses of all the variables in this model. This suggests that standard macroeconomic frameworks with financial frictions seem to fall short of explaining the empirical IRFs to credit demand shocks, raising the question on how these models could be modified to allow for the modelling of credit demand shocks in future research.

Chapter 5

Concluding Remarks

In this thesis, I attempted to contribute to the understanding of the interactions between financial markets and the macroeconomy, by highlighting the quantitative importance of disturbances that originate from the demand side of credit markets and analysing the channels through which these loan demand shocks propagate to the real economy.

A survey of the macro-finance literature that incorporates financial frictions first allowed me to distinguish between financial shocks that originate from the supply side of credit and those stemming from the demand side. Notably, I emphasized that the channels through which the demand side shocks propagate to the economy are different from the financial accelerator mechanism at play in most macro-financial frameworks that study the credit supply side shocks. Besides, while the supply-side literature extensively grew since the crisis, works that analyse both the effects for economic activity and the policy implications of demand-side financial shocks are quite scant.

In an attempt to reduce this gap, I then undertook a quantitative evaluation of the relative importance of credit demand and supply shocks, combining survey data on loan demand and supply schedules with standard macroeconomic variables in a Bayesian VAR setting where identification is performed using both sign and zero restrictions. I found that credit demand shocks are as important as credit supply shocks for the UK economy, a positive unit shock of either kind resulting in a 10 bp increase in output. This finding, which is robust across several alternative specifications, is at odds with the common belief that credit demand shocks are not relevant for business cycle fluctuations and therefore should not retain policy makers' attention.

Taking it further, I lastly analysed the transmission channels of these loan demand shocks

in a DSGE framework, and found that they propagate to the economy through both the Fisher deflation and collateral channels. The combined effects of these two channels are further amplified to the economy in the presence of occasionally binding borrowing constraints.

With these analyses of credit demand shocks, a large research agenda opens up. One possible direction is to extend this thesis towards a deeper analysis of the importance of loan demand shocks for economic fluctuations. Such analysis could be done through an investigation of credit demand channels along various dimensions as dictated by the diverse forms of heterogeneity encountered in credit markets. This would involve matching survey micro data on loan demand and supply schedules with individual bank level balance-sheets data as an attempt of an alternative identification strategy for credit demand and supply shocks, and constructing an aggregate measure of credit demand that would then be used for the quantitative evaluation of loan demand shocks. Another route could be through the determination of what shocks lead to a higher endogenous response of credit demand, through a Bayesian estimation of a medium scale DSGE model. Such project could be motivated by the observation that changes in loan demand do not only occur as exogenous disturbances affecting directly the financial sector, but can also be endogenous responses to different shocks originated in other sectors of the economy. This could be of great interest to the policy maker who usually has more instruments and options at its disposal to tackle credit supply related disturbances than credit demand shocks. Such analysis may help with the formulation of suitable policies that account for changes in loan demand by firms and households.

Appendix A

Appendices to Chapter 3

A.1 Detailed Variables Description and Data Sources

Variable	Survey Question	Variable's Measure
Credit demand	How has demand for loans of type X to your bank changed over the last 3 months relative to the previous 3 months?	Difference between the net percentage balance of lenders reporting a higher demand for loans of type X and those reporting a lower demand.
Credit supply	How has the availability of loans of type X at your bank changed over the last 3 months relative to the previous 3 months?	Difference between the net percentage balance of lenders reporting a higher availability of loans of type X and those reporting a lower availability.
Credit Supply Factors	How has each of the following factors contributed to changes in credit availability: changing economic outlook, changing borrower's sector-specific risks, market share objectives, market pressures from capital markets, changing appetite for risk, tight wholesale funding conditions?	Difference between the net percentage balance of lenders reporting a higher change for each of these factors and those reporting a lower change.
Credit Demand Factors	How has each of the following factors contributed to changes in credit demand: mergers and acquisitions, capital investment, inventory finance, balance sheet restructuring, commercial real estate?	Difference between the net percentage balance of lenders reporting a higher change for each of these factors and those reporting a lower change.

TABLE A.1: The Bank of England Credit Conditions Survey used Questions

Note: The detailed questionnaires, data, and guide for the survey can be found on the Bank of England website at http://www.bankofengland.co.uk/publications/Pages/other/monetary/creditconditions.aspx.

Variable	Description	Source
Real GDP	Gross Domestic Product, chained volume measures, seasonally adjusted.	Quarterly National Accounts time series dataset (QNA) from the Office for National Statistics (ONS): https://www.ons.gov.uk/economy/ grossdomesticproductgdp/ timeseries/abmi/qna
Inflation	Implied GDP deflator at market prices, seasonally adjusted index.	QNA time series dataset, from the ONS: https://www.ons.gov.uk/ economy/grossdomesticproductgdp/ timeseries/18gg/qna
Policy Rate	End quarter level of Gilt repo interest rate, 3 months.	Interest and Exchange rates, from the BoE Interactive Database, code = IUQGR3M, https://www. bankofengland.co.uk/boeapps/iadb/
Loan Supply	Average of the changes in business, mortgage, and consumer credit availability, each of which is weighted by its respective share computed using seasonally adjusted and deflated sterling lendings data from the Bank of England Money and Credit Statistics.	Bank of England Credit Conditions Survey: https://www.bankofengland. co.uk/credit-conditions-survey/ 2018/2018-q1
Loan Demand	Average of the changes in business, mortgage, and consumer loan demands, each of which is weighted by its respective share as before.	Bank of England Credit Conditions Survey: https://www.bankofengland. co.uk/credit-conditions-survey/ 2018/2018-q1
Loans Volume	Quarterly amounts outstanding of monetary financial institutions' sterling net lending to private non-financial corporations and households, seasonally adjusted.	Bank of England Interactive Database, code = LPQBE33, https://www. bankofengland.co.uk/boeapps/iadb/
Loans Volume Growth Rate	Quarterly growth rate of monetary financial institutions' sterling net lending to private non-financial corporations and households, seasonally adjusted.	Bank of England Interactive Database, code = LPQB3B7, https://www. bankofengland.co.uk/boeapps/iadb/
Lendings by Loan Type	Quarterly amounts outstanding of monetary financial institutions' sterling net lending for business, mortgage, and consumer loans, seasonally adjusted. They are used to compute the respective shares of each type of loan.	Bank of England Interactive Database, codes: LPQBC57 (business), LPQBC44 (households), LPQVVYI (consumer), LPQBC44 - LPQVVYI (mortgage), https://www. bankofengland.co.uk/boeapps/iadb/
Bank lending Rate	Composite rate based on the end-of-quarter average bank lending rate for business, mortgage, and consumer loans from the BoE Money and Credit Statistics.	Bank of England Interactive Database, codes: CFMBJ82 (business), IUMTLMV (mortgage), IUMCCTL + IUMHPTL (consumer), https://www. bankofengland.co.uk/boeapps/iadb/
Nominal GDP	Gross Domestic Product at market prices, current price, seasonally adjusted.	QNA time series dataset, from the ONS: https://www.ons.gov.uk/ economy/grossdomesticproductgdp/ timeseries/ybha/qna

TABLE A.2: Variables Description and Data Sources

A.2 Model's Details and Estimation

The structural VAR(p) representation in equation (1.2) can be compactly written for $1 \le t \le T$ as

$$B_0 y_t = B_+ x_t + \omega_t \tag{A.1}$$

where $B_+ = [B_1 \dots B_p c]$ and $x'_t = [y'_{t-1} \dots y'_{t-p} 1]$ for $t = 1, \dots, T$. The dimension of B_+ is $n \times m$, where m = np + 1. The reduced-form implied by equation (1.1) is then compactly given, for $1 \le t \le T$, by

$$y_t = Ax_t + \epsilon_t \tag{A.2}$$

where $A = B_0^{-1}B_+$, $\epsilon_t = B_0^{-1}\omega_t$, and $E(\epsilon_t\epsilon_t') = \Sigma = B_0^{-1}B_0^{-1'} = (B_0'B_0)^{-1}$. The matrices A and Σ are the reduced-form parameters, while B_0 and B_+ are the structural parameters.

To solve the identification problem, we impose both sign and zero restrictions on the structural parameters of the model as fully explained in section 3.3.2. These identifying restrictions fulfill the following necessary and sufficient conditions for identification: the necessary order condition as spelled out by Rothenberg (1971) states that the number of zero restrictions for all the nstructural shocks is greater than or equal to n(n-1)/2, whereas the sufficient rank condition as formulated in Rubio-Ramirez et al. (2010) implies for our partial identification, that there must be an ordering of the structural shocks such that there are at least (n-j) zero restrictions on the *j*th structural shock and at least one sign restriction on the IRFs to this structural shock for $1 \leq j \leq k$ (where k is the number of partially identified structural shocks).¹

We summarize the identifying restrictions in matrices S_j and Z_j , where S_j is a $s_j \times r$ matrix of full row rank $s_j \ge 0$ (s_j being the number of sign restrictions on horizon h IRFs to the jth structural shock), and Z_j a $z_j \times r$ matrix of full row rank z_j with $0 \le z_j \le n - j$ (z_j being the number of zero restrictions associated with the jth structural shock), for $1 \le j \le n$. r is equal to the number of rows in the matrix of structural impulse responses to be restricted, which is denoted by $F(B_0, B'_+)$. The matrix S_j represents the sign restrictions on the jth structural shock, whereas the matrix Z_j summarizes the zero restrictions on the jth structural shock for $1 \le j \le n$. In particular, we assume as in Arias et al. (2018) that the structural parameters (B_0, B_+) will satisfy the sign restrictions if and only if $S_j F(B_0, B'_+)e_j > 0$, and the zero restrictions if and

¹In the case of a full identification of all the structural shocks in the model, the sufficient rank condition implies that there must be an ordering of the structural shocks such that there are at least (n - j) zero restrictions on the *j*th structural shock, for $1 \le j \le n$, and at least one sign restriction on the IRFs to each structural shock. However, in our application and several others in the literature, there are typically only a few zero restrictions and so there will be less than (n - j) zero restrictions on the *j*th structural shock.

only if $Z_j F(B_0, B'_+)e_j = 0$, for $1 \le j \le n$, where e_j is the *j*th column of the identity matrix I_n , whereas the function F is used to stack the IRFs at all the desired horizons (i.e., the matrix of structural impulse responses to be restricted).

In particular, the zero restrictions rely on timing assumptions and a Cholesky decomposition of the reduced-form VAR covariance matrix. More precisely, the Cholesky decomposition orthogonalizes the reduced-form errors to obtain mutually uncorrelated structural errors. This is typically performed as follows. One first defines a lower-triangular $n \times n$ matrix P with positive main diagonal such that $PP' = \Sigma$. P is the Cholesky decomposition of Σ . Then it follows immediately from the condition $\Sigma = B_0^{-1}B_0^{-1'}$ that $B_0^{-1} = P$. This orthogonalization is appropriate as long as the recursive structure embodied in P can be justified on economic grounds.

As for the signs restrictions, they involve the use of the QR decomposition of an $n \times n$ random matrix W which elements are *i.i.d.* N(0, 1). In particular, Rubio-Ramirez et al. (2010) show that if W = QR is the QR decomposition of W with the diagonal of R normalized to be positive, then the $n \times n$ random matrix Q is orthogonal (i.e., its columns are orthogonal unit vectors such that $QQ' = Q'Q = I_n$, which is equivalent to $Q' = Q^{-1}$), and is a draw from the uniform distribution over the set of all $n \times n$ orthogonal matrices $\mathbf{O}(n)$. Given the reduced-form parameters and the lower-triangular Cholesky decomposition P, one can then generate a large number of candidate solutions for B_0^{-1} as PQ where Q is obtained from a random draw of W. Once enough candidate solutions for B_0^{-1} are obtained, one only retains those solutions which yield a structural impact matrix that agrees with the imposed sign restrictions.

Equation (A.2) above can alternatively be written in the following orthogonal reduced-form parametrization, for $1 \le t \le T$:

$$y_t = Ax_t + h(\Sigma)' Q\omega_t \tag{A.3}$$

where A and Σ are the reduced-form parameters defined previously, Q is an orthogonal matrix, and $h(\Sigma)$ is the Cholesky decomposition of the covariance matrix Σ satisfying $h(\Sigma)h(\Sigma)' = \Sigma$.

We are interested in making draws from the structural parametrization conditional on the sign and zero restrictions. However, conditioning on both the sign and zero restrictions imposes non-linear constraints on the structural parameters that are dealt with by converting the zero restrictions into linear restrictions on the columns of the orthogonal matrix Q. In order to do that, we follow Arias et al. (2018) and start by defining a mapping between the orthogonal

reduced-form reduced-form parameters (A, Σ, Q) and the structural parameters (B_0, B_+) , given equations (A.1), (A.3) and the Cholesky decomposition h:

$$f_h(B_0, B_+) = \left(B_0^{-1}B_+, (B_0'B_0)^{-1}, h((B_0'B_0)^{-1})B_0\right)$$

where $A = B_0^{-1}B_+$, $\Sigma = (B'_0B_0)^{-1}$, and $Q = h((B'_0B_0)^{-1})B_0$ by direct computation.² Besides, the function f_h is invertible, with inverse defined by

$$f_h^{-1}(A, \Sigma, Q) = \left(h(\Sigma)^{-1}Q, h(\Sigma)^{-1}QA\right)$$

where one can easily show that $h(\Sigma)^{-1}Q = B_0$ and $h(\Sigma)^{-1}QA = B_+$.

Then, given the definition of f_h^{-1} and an admissibility condition which states that a function $F(B_0, B'_+)$ is admissible if and only if for any $Q \in \mathbf{O}(n)$, $F(B_0Q, B'_+Q) = F(B_0, B'_+)Q$, the zero restrictions associated with the *j*th structural shock expressed as linear restrictions on the *j*th column of the orthogonal matrix Q will hold if and only if

$$Z_j F(f_h^{-1}(A, \Sigma, Q)) e_j = Z_j F(f_h^{-1}(A, \Sigma, I_n)) Q e_j = 0 \quad \text{for } 1 \le j \le n.$$

In the estimation process of our model, which is done using a Bayesian approach, we use a family of conjugate distributions as is common in this Bayesian VAR (BVAR henceforth) analysis.³ In particular, following Arias et al. (2018) and most of the recent BVAR literature, we use the Normal-Inverse-Wishart (NIW henceforth) family of distributions which is conjugate for the reduced-form representation in equation (A.2). This family of distributions consists of a normal distribution for the slope parameters contained in matrix A, and an inverse-Wishart distribution for the covariance matrix Σ .

Hence, a Normal-Inverse-Wishart family of distributions over the reduced-form parameters (A, Σ) is characterized by the four following parameters: a scalar $\nu > n$ and an $n \times n$ symmetric and positive definite matrix Φ that determine the Inverse-Wishart distribution; and an $m \times n$ matrix Ψ and an $m \times m$ symmetric and positive definite matrix Ω that characterize the normal

²A key issue is to understand how to transform densities in the defined mapping between (B_0, B_+) and (A, Σ, Q) , conditional on both sign and zero restrictions. Arias et al. (2018) propose adequate change of variables formulas to handle this problem. Details of the change of variables results can be found in section 2.4 of their paper. One of Arias et al. (2018)'s key contributions has been to propose a generalization of the change of variables theorem (Theorem 3 in the paper) to settings which combine sign and zero restrictions.

 $^{^{3}}$ A family of distributions is conjugate if the prior distribution being a member of this family implies that the posterior distribution is also a member of the family.

distribution. More formally, $\Sigma \sim IW(\nu, \Phi)$ with ν degrees of freedom and scale matrix Φ , whereas $A \mid \Sigma \sim N(\Psi, \Sigma \otimes \Omega)$.

If the prior distribution over the reduced-form parameters is $NIW(\bar{\nu}, \bar{\Phi}, \bar{\Psi}, \bar{\Omega})$, then the corresponding posterior distribution, obtained by multiplying the prior density by the likelihood function, is $NIW(\tilde{\nu}, \tilde{\Phi}, \tilde{\Psi}, \tilde{\Omega})$ with

$$\begin{split} \tilde{\nu} &= T + \bar{\nu} \\ \tilde{\Omega} &= (X'X + \bar{\Omega}^{-1})^{-1} \\ \tilde{\Psi} &= \tilde{\Omega}(X'Y + \bar{\Omega}^{-1}\bar{\Psi}) \\ \tilde{\Phi} &= Y'Y + \bar{\Phi} + \bar{\Psi}'\bar{\Omega}^{-1}\bar{\Psi} - \tilde{\Psi}'\tilde{\Omega}^{-1}\tilde{\Psi} \end{split}$$

where $Y = [y_1 \dots y_T]'$ and $X = [x_1 \dots x_T]'$.

For the choice of the prior for the NIW distribution, we follow Giannone et al. (2015) who combine three of the most commonly used conjugate priors in the literature - the Minnesota, sum-of-coefficients, and dummy-initial-observation priors - in order to make inferences about the informativeness of BVARs' prior distributions, and show that this leads to more accurate and economically plausible IRFs. In particular we choose the following parameter values for my baseline's prior specification: $\bar{\nu} = n$, $\bar{\Omega} = I_m$, $\bar{\Phi} = I_n$, and $\bar{\Psi} = 0_{m,n}$.

If $\pi(Q \mid A, \Sigma)$ is a conditional uniform density over $\mathbf{O}(n)$, then prior densities of the form $NIW_{(\bar{\nu},\bar{\Phi},\bar{\Psi},\bar{\Omega})}(A,\Sigma)\pi(Q \mid A,\Sigma)$ over the orthogonal reduced-form parametrization with distribution denoted by $UNIW(\nu, \Phi, \Psi, \Omega)$, will be conjugate. Given the density over the orthogonal reduced-form parametrization $UNIW_{(\nu,\Phi,\Psi,\Omega)}(A,\Sigma,Q)$ and the previously defined mapping function $f_h(B_0, B_+) = (A, \Sigma, Q)$, the density over the structural parametrization induced by the UNIW density is

$$NGN_{(\nu,\Phi,\Psi,\Omega)}(B_{0},B_{+}) = UNIW_{(\nu,\Phi,\Psi,\Omega)}(f_{h}(B_{0},B_{+}))v_{f_{h}}(B_{0},B_{+})$$

$$\propto |det(B_{0})|^{\nu-n} exp\left[-\frac{1}{2}vec(B_{0})'(I_{n}\otimes\Phi)vec(B_{0})\right] \qquad (A.4)$$

$$\times exp\left[-\frac{1}{2}vec(B_{+}-\Psi B_{0})'(I_{n}\otimes\Omega)^{-1}vec(B_{+}-\Psi B_{0})\right]$$

for which the corresponding distribution is the family of conjugate distributions Normal-Generalized-Normal denoted by $NGN(\nu, \Phi, \Psi, \Omega)$. Drawing from this distribution is equivalent to independently drawing (A, Σ, Q) from a Uniform-Normal-Inverse-Wishart distribution $UNIW_{(\nu, \Phi, \Psi, \Omega)}(A, \Sigma, Q)$ and then transforming the draws into the structural parameters (B_0, B_+) using f_h^{-1} . Besides,

$$v_{f_h}(B_0, B_+) = 2^{\frac{n(n+1)}{2}} |det(B_0)|^{-(2n+m+1)}$$

is the volume element of f_h at (B_0, B_+) , and is essential for drawing from the density over the structural parametrization when zero restrictions are imposed on top of sign restrictions.⁴

Finally, the independent draws from the Uniform-Normal-Inverse-Wishart posterior distribution that satisfy the sign and zero restrictions are simulated using an Importance sampler, before being ultimately transformed into the structural parameters (B_0, B_+) via the mapping function f_h^{-1} , and used for inference.

 $^{^{4}}$ For a more formal definition of the volume element and the technical conditions of its use in a setting where zero restrictions are imposed in addition to sign restrictions, refer to Theorem 3 in section 2.4. of Arias et al. (2018).

A.3 Arias et al. (2018)'s Sign and Zero Restrictions Algorithm Steps.

Arias et al. (2018)'s algorithm makes independent draws from the Normal-Generalized-Normal posterior distributions over the structural parametrization conditional on the sign and zero restrictions. It proceeds as follows:

- 1. Draw (A, Σ) independently from the $NIW(\nu, \Phi, \Psi, \Omega)$ distribution.
- 2. Find an orthogonal matrix Q such that $f_h^{-1}(A, \Sigma, Q) = (B_0, B_+)$ satisfies the zero restrictions. This is done as follows:
 - (a) Let X be a $n \times n$ matrix of independent N(0, 1) draws, and \hat{Q} obtained by QR decomposition of X. Moreover, define $R_1 = Z_1 F(B_0, B'_+)$ and for j = 2, ..., n,

$$R_{j} = \begin{bmatrix} Z_{j}F(B_{0}, B_{+}^{'})\\ \tilde{Q}_{j-1} \end{bmatrix}$$

where $F(B_0, B'_+)$ denotes the matrix of structural impulse responses to be restricted, Z_j the corresponding matrix of zero restrictions, and $\tilde{Q}_{j-1} = [\tilde{q}_1 \dots \tilde{q}_{j-1}].$

- (b) Let j = 1. Construct R_j, and find the matrix K_{j-1} whose columns form an orthonormal basis for the null space of R_j (this is done by applying the Matlab function null to R_j).
- (c) Draw y_j from the standard normal distribution on $R^{n+1-j-z_j}$ where $(n+1-j-z_j)$ is the number of columns in K_{j-1} .
- (d) Then, set $w_j = \frac{y_j}{\|y_j\|}$ and compute $q_j = K_j w_j$, where $\|\cdot\|$ is the Euclidean norm.
- (e) if j = n, stop. Otherwise, let j = j + 1 and move to step b.
- 3. Construct $Q = [q_1 \dots q_n]$, and check if $S_j F(f_h^{-1}(A, \Sigma, Q))e_j > 0$, for $1 \le j \le n$.
- 4. (i) If (B_0, B_+) satisfies the sign restrictions, set its importance weight to

$$\frac{NGN_{(\nu,\Phi,\Psi,\Omega)}(B_0,B_+)}{NIW_{(\nu,\Phi,\Psi,\Omega)}(A,\Sigma)v_{(g\circ f_h)|\mathbf{Z}}(B_0,B_+)} \propto \frac{|\det(B_0)|^{-(2n+m+1)}}{v_{(g\circ f_h)|\mathbf{Z}}(B_0,B_+)}$$

where $NGN_{(\nu,\Phi,\Psi,\Omega)}(B_0, B_+) \equiv UNIW_{(\nu,\Phi,\Psi,\Omega)}(f_h(B_0, B_+))v_{f_h}(B_0, B_+)$ from equation (38) with $(A, \Sigma, Q) = f_h(B_0, B_+)$, **Z** denotes the set of all structural parameters that satisfy the zero restrictions, and $v_{(g \circ f_h)|\mathbf{Z}}(B_0, B_+)$ is the volume element of $g \circ f_h$ at (B_0, B_+) .

- (*ii*) Otherwise, set the importance weight to zero.
- 5. Return to Step 1 until the required number of draws has been obtained.
- 6. Re-sample with replacement using the importance weights so as to have unweighted and independent draws.

A.4 Further Robustness and Additional Exercises.

A.4.1 Alternative Measure of the Loans Volume's Growth Rate

In this exercise, we use the loan approval rate from the BoE CCS as an alternative measure of the loans volume's growth rate in the 6-variable VAR version of the model, and find that our baseline result is robust to this alternative specification, as illustrated in FIGURE A.1 below.

> FIGURE A.1: Impulse responses for the model with loan approval rate (a) Credit Demand Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

A.4.2 Use of Alternative Data-set

As another robustness test with proxy variables, we use a different UK data set, namely the one constructed by Gambetti and Musso (2017)'s to analyze the effects of loan supply shocks using a time-varying parameters (TVP) VAR, and find qualitatively similar results.

FIGURE A.2: Impulse responses for the model with Gambetti and Musso (2017)'s UK data set (a) Credit Demand Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

A.4.3 Heterogeneous Loan-Types Credit Transmission Channels with Credit volume's growth rate

Finally, our conclusion in section 1.4.3 that the UK economy is mostly driven by the mortgage loans market, is unchanged when we use the loans volume's growth rate in lieu of the credit variables from the BoE CCS.

FIGURE A.3: Impulse responses for the model with heterogeneous loan-types

(a) Credit Demand Shock



Note: Panel (a) represents the IRFs to a one standard deviation credit demand shock, whereas panel (b) illustrates the IRFs for a one standard deviation credit supply shock. The solide curves represent the point-wise posterior medians, and the shaded areas represent the 68% equally tailed point-wise probability bands. The figure is based on more than 1,000 independent draws from an importance sampler using Arias et al. (2018)'s algorithm.

A.4.4 Residuals Plot for Credit Supply and Demand



FIGURE A.4: Loan Supply and Demand Innovations over the Sample Period

Note: This figure plots our constructed aggregate loan supply and demand variables innovations over the sample period.

Appendix B

Appendices to Chapter 4

B.1 The Model's detailed Equilibrium Conditions

B.1.1 Patient Households

$$\lambda_{p,t} = \frac{(1-a_p)}{(c_{p,t}(i) - a_p C_{t-1})}$$
(B.1)

$$\frac{\varphi}{h_{p,t}(i)} = \lambda_{p,t} q_{h,t} + \beta_p E_t q_{h,t+1} \lambda_{p,t+1}$$
(B.2)

$$\lambda_{p,t} = \beta_p E_t \frac{(1+r_{d,t})\lambda_{p,t+1}}{\pi_{t+1}}$$
(B.3)

$$l_{p,t}(i)^{\phi} = w_{p,t}\lambda_{p,t} \tag{B.4}$$

$$c_{p,t}(i) + q_{h,t}(h_{p,t}(i) - h_{p,t-1}(i)) + d_{p,t}(i) = w_{p,t}l_{p,t}(i) + \frac{(1 + r_{d,t-1})}{\pi_t}d_{p,t-1}(i) + J_{R,t}(i)$$
(B.5)

B.1.2 Impatient Households

$$\lambda_{i,t} = \frac{(1-a_i)}{(c_{i,t}(i) - a_i C_{t-1})} \tag{B.6}$$

$$\frac{\varphi}{h_{i,t}(i)} = \lambda_{i,t}q_{h,t} + \beta_i E_t q_{h,t+1}\lambda_{i,t+1} - \mu_{i,t}m_{i,t}E_t q_{h,t+1}\pi_{i,t+1}$$
(B.7)

$$\lambda_{i,t} = \beta_i E_t \frac{(1+r_{bh,t})\lambda_{i,t+1}}{\pi_{t+1}} + \mu_{i,t}(1+r_{bh,t})$$
(B.8)

$$l_{i,t}(i)^{\phi} = w_{i,t}\lambda_{i,t} \tag{B.9}$$

$$c_{i,t}(i) + q_{h,t}(h_{i,t}(i) - h_{i,t-1}(i)) + \frac{(1+r_{bh,t-1})}{\pi_t} b_{i,t-1}(i) = w_{i,t}l_{i,t}(i) + b_{i,t}(i)$$
(B.10)

$$(1 + r_{bh,t})b_{i,t}(i) = m_{i,t}E_t[q_{h,t+1}\pi_{t+1}h_{i,t}(i)]$$
(B.11)

B.1.3 Entrepreneurs

$$\lambda_{e,t} = \frac{(1 - a_e)}{(c_{e,t}(i) - a_e C_{t-1})} \tag{B.12}$$

$$\mu_{e,t}(i)m_{e,t}E_tq_{k,t+1}\pi_{t+1}(1-\delta_k) + \beta_e E_t\lambda_{e,t+1}(q_{t+1}(1-\delta_k) + r_{k,t+1}) = \lambda_{e,t}q_{k,t}$$
(B.13)

$$w_{p,t} = \psi(1-\alpha) \frac{y_{e,t}(i)}{l_{pe,t}(i)x_t}$$
 (B.14)

$$w_{i,t} = (1 - \psi)(1 - \alpha) \frac{y_{e,t}(i)}{l_{ie,t}(i)x_t}$$
(B.15)

$$\lambda_{e,t} = \beta_e E_t \frac{(1+r_{be,t})\lambda_{e,t+1}}{\pi_{t+1}} + \mu_{e,t}(1+r_{be,t})$$
(B.16)

$$c_{e,t}(i) + w_{p,t}l_{pe,t}(i) + w_{i,t}l_{ie,t}(i) + \frac{(1+r_{be,t-1})}{\pi_t}b_{e,t-1}(i) + q_{k,t}k_{e,t}(i) = \frac{y_{e,t}(i)}{x_t} + b_{e,t}(i) + q_{k,t}(1-\delta_k)k_{e,t-1}(i)$$
(B.17)

$$y_{e,t}(i) = A_t k_{e,t-1}(i)^{\alpha} \left[l_{pe,t}(i)^{\psi} l_{ie,t}(i)^{(1-\psi)} \right]^{(1-\alpha)}$$
(B.18)

$$(1 + r_{be,t})b_{e,t}(i) = m_{e,t}E_t[q_{k,t+1}\pi_{t+1}(1 - \delta_k)k_{e,t}(i)]$$
(B.19)

$$r_{k,t}(i) \equiv \frac{\alpha A_t k_{e,t-1}(i)^{(\alpha-1)} \left[l_{pe,t}(i)^{\psi} l_{ie,t}(i)^{(1-\psi)} \right]^{(1-\alpha)}}{x_t}$$
(B.20)

B.1.4 Banks

$$b_t(j) = d_{b,t}(j) + k_{b,t}(j)$$
 (B.21)

$$r_{b,t} = -\kappa_{kb} \Big(\frac{k_{b,t}(j)}{b_t(j)} - \nu \Big) \Big(\frac{k_{b,t}(j)}{b_t(j)} \Big)^2 + r_t$$
(B.22)

$$\pi_t k_{b,t}(j) = (1 - \delta_b) k_{b,t-1}(j) + j_{b,t-1}(j)$$
(B.23)

$$r_{bH,t} = r_{bE,t} = r_t - \kappa_{k_b} \Big(\frac{k_{b,t}(j)}{b_t(j)} - \nu \Big) \Big(\frac{k_{b,t}(j)}{b_t(j)} \Big)^2 + \mu_b = r_{b,t} + \mu_b$$
(B.24)

$$j_{b,t}(j) = r_{bH,t}b_{H,t}(j) + r_{bE,t}b_{E,t}(j) - r_td_{b,t}(j) - \frac{\kappa_{k_b}}{2} \left(\frac{k_{b,t}(j)}{b_t(j)} - \nu\right)^2 k_{b,t}(j)$$
(B.25)

B.1.5 Capital Goods Producers

$$1 = q_{k,t} \left[1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 - \kappa_I \left(\frac{I_t}{I_{t-1}} - 1 \right) \left(\frac{I_t}{I_{t-1}} \right) \right] + \beta_e E_t \left[\frac{\lambda_{e,t+1}}{\lambda_{e,t}} q_{k,t+1} \kappa_I \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right]$$
(B.26)

$$K_t = (1 - \delta_k) K_{t-1} + \left[1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t$$
(B.27)

B.1.6 Retailers

$$\kappa_P(\pi_t - \pi)\pi_t + \varepsilon_y - \frac{\varepsilon_y}{x_t} - 1 = \beta_p E_t \left[\frac{\lambda_{p,t+1}}{\lambda_{p,t}} \kappa_P(\pi_{t+1} - \pi)\pi_{t+1} \frac{Y_{t+1}}{Y_t} \right]$$
(B.28)

$$J_{R,t} = Y_t \left[1 - \frac{1}{x_t} - \frac{\kappa_P}{2} (\pi_t - \pi)^2 \right]$$
(B.29)

B.1.7 Monetary Policy

$$(1+r_t) = (1+r)^{(1-\phi_r)} (1+r_{t-1})^{\phi_r} \left(\frac{\pi_t}{\pi}\right)^{\phi_\pi (1-\phi_r)} \left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y (1-\phi_r)} (1+\varepsilon_{r,t})$$
(B.30)

B.1.8 Markets Clearing Conditions and Aggregation

$$Y_t = C_t + [K_t - (1 - \delta_k)K_{t-1}]$$
(B.31)

$$Y_t = \gamma_e y_t \tag{B.32}$$

$$C_t = \gamma_p c_{p,t} + \gamma_i c_{i,t} + \gamma_e c_{e,t} \tag{B.33}$$

$$K_t = \gamma_e k_{e,t} \tag{B.34}$$

$$D_t = \gamma_p d_{p,t} = \gamma_b d_{b,t} \tag{B.35}$$

$$B_{e,t} = \gamma_b b_{E,t} \tag{B.36}$$

$$B_{h,t} = \gamma_b b_{H,t} \tag{B.37}$$

$$B_t = B_{h,t} + B_{e,t} \tag{B.38}$$

$$B_t = D_t + K_{B,t} \tag{B.39}$$

$$K_{B,t} = \gamma_b k_{b,t} \tag{B.40}$$

$$J_{B,t} = \gamma_b j_{b,t} \tag{B.41}$$

$$\gamma_e l_{pe,t} = \gamma_p l_{p,t} \tag{B.42}$$

$$\gamma_e l_{ie,t} = \gamma_i l_{i,t} \tag{B.43}$$

$$\overline{h} = h_{p,t} + h_{i,t} \tag{B.44}$$

B.2 The Model's Steady State Derivation

The non-stochastic steady-state gross inflation is given by $\pi = 1.005$. Given π , equation (B.3) from Appendix **B.1** allows the computation of the steady-state value of the deposit rate as

$$r_d = \frac{\pi}{\beta_p} - 1 \tag{B.45}$$

which is also equal to the policy rate by assumption: $r = r_d$.

The steady-state value of households' shadow price of borrowing $\frac{\mu_i}{\lambda_i}$ is derived from equation (B.8) as

$$\frac{\mu_i}{\lambda_i} = \frac{1}{\mu_b + (1/\beta_p)} - \frac{\beta_i}{\pi} \tag{B.46}$$

where I have made use of the assumption that in steady-state, the bank capital-to-asset ratio does not deviate from the exogenous target, i.e., $\frac{k_b}{b} = \nu$, so that equations (B.22) and (B.24) imply that the wholesale bank steady-state lending rate $r_b = r = r_d$ and the retail bank's one for households is $r_{bh} = r_b + \mu_b$, which is also equal to r_{be} by assumption. Similarly to (B.46), I use equation (B.16) to compute the steady-state value of entrepreneurs' shadow price of borrowing as

$$\frac{\mu_e}{\lambda_e} = \frac{1}{\mu_b + (1/\beta_p)} - \frac{\beta_e}{\pi} \tag{B.47}$$

Besides, by still using $\frac{k_b}{b} = \nu$ along with equation (B.23), I obtain the steady-state value of the bank profit-to-asset ratio as

$$\frac{j_b}{b} = \nu(\pi - 1 + \delta_b) \tag{B.48}$$

whereas the bank balance-sheet constraint (B.21) and $\frac{k_b}{b} = \nu$ yield a steady-state value of the bank wholesale loans-to-asset ratio of

$$\frac{d_b}{b} = 1 - \nu \tag{B.49}$$

Next, I compute the steady-state value of the ratio of physical capital to output as

$$\frac{k_e}{Y} = \frac{\alpha \beta_e}{x[1 - m_e(1 - \delta_k)\pi \frac{\mu_e}{\lambda_e} - \beta_e(1 - \delta_k)]}$$
(B.50)

where the steady-state markup of the retail sector x is derived from equation (B.28) as $x = \frac{\varepsilon_y}{\varepsilon_y - 1}$, $Y = y_e$ from equation (B.32), m_e is the entrepreneurs' steady-state DTV ratio calibrated from the data, $\frac{\mu_e}{\lambda_e}$ is given by equation (B.47) above, and where I also made use of equation (B.18) and the fact that the steady-state value of the price of physical capital $q_k = 1$ from equation (B.26).

Then, using equation (B.27) and the previous one, the steady-state value of the ratio of investment to output is derived as

$$\frac{I}{Y} = \delta_k \frac{k_e}{Y} \tag{B.51}$$

where I used the fact that in steady-state, $K = k_e$ from equation (B.34).

Using again equation (B.47) as well as equation (B.19), I compute the steady-state ratio of entrepreneurs' borrowing to output as

$$\frac{b_e}{Y} = \left[\frac{m_e(1-\delta_k)\pi}{\mu_b + (1/\beta_p)}\right] \frac{k_e}{Y}$$
(B.52)

I can then derive the steady-state ratio of entrepreneurs' consumption to output $\frac{c_e}{Y}$, using equations (B.17), (B.14), (B.15), (B.47) and (B.50). After some algebra, I get

$$\frac{c_e}{Y} = \frac{\alpha}{x} + \left[1 - \frac{(1+r_{be})}{\pi}\right]\frac{b_e}{Y} - \delta_k \frac{k_e}{Y} \tag{B.53}$$

Next, I first use equation (B.7) to obtain the steady-state ratio of impatient households' housing value to output as

$$\frac{q_h h_i}{Y} = \left[\frac{\varphi}{(1-\beta_i) - m_i(\mu_i/\lambda_i)\pi}\right] \frac{c_i}{Y}$$
(B.54)

and then, using equation (B.11), I derive the steady-state value of the ratio of impatient households' borrowing to output as

$$\frac{b_i}{Y} = \left[\frac{m_i \pi}{\mu_b + (1/\beta_p)}\right] \frac{q_h h_i}{Y} \tag{B.55}$$

Using these two previous equations along with equations (B.10) and (B.15), some algebraic manipulations allow me to derive the steady-state ratio of impatient households' consumption to

output as

$$\frac{c_i}{Y} = \frac{(1-\psi)(1-\alpha)}{x \left[1 - \left(1 - \frac{(1+r_{bh})}{\pi}\right) \left(\frac{m_i \pi}{\mu_b + (1/\beta_p)}\right) \left(\frac{\varphi}{(1-\beta_i) - m_i(\mu_i/\lambda_i)\pi}\right)\right]}$$
(B.56)

that is, a function of the steady-state value r_{bh} already determined above, of primitive parameters and the fixed steady-states π and m_i (the impatient households' steady-state DTV ratio, calibrated from the data). Therefore, it can be plugged back into equations (B.54) and (B.55) to determine $\frac{q_h h_i}{V}$ and $\frac{b_i}{V}$.

Next, I use the aggregate resources constraint (B.31) and equation (B.33) together with the previously determined equations (B.51), (B.53) and (B.56) to deduct patient households' consumption to output ratio as:

$$\frac{c_p}{Y} = 1 - \frac{c_i}{Y} - \frac{c_e}{Y} - \frac{I}{Y}$$
 (B.57)

Then, given (B.57), I use equation (B.2) to derive the steady-state ratio of patient households' housing value to output as

$$\frac{q_h h_p}{Y} = \left[\frac{\varphi}{(1-\beta_p)}\right] \frac{c_p}{Y} \tag{B.58}$$

which, together with equation (B.54), allow me to compute the steady-state value of the ratio of house price to output as

$$\frac{q_h}{Y} = \frac{q_h h_p}{Y} + \frac{q_h h_i}{Y} = \left[\frac{\varphi}{(1-\beta_p)}\right] \frac{c_p}{Y} + \left[\frac{\varphi}{(1-\beta_i) - m_i(\mu_i/\lambda_i)\pi}\right] \frac{c_i}{Y}$$
(B.59)

where I used the fact that $h_p + h_i = \bar{h} = 1$. Then, given (B.59) and (B.60), I deduct the steady-state patient households' quantity of houses as

$$h_p = \frac{q_h h_p}{Y} \left(\frac{q_h}{Y}\right)^{-1} \tag{B.60}$$

from which h_i is in turn deducted as $h_i = 1 - h_p$.

Besides, given (B.57), I use equations (B.4) and (B.14) to equate the steady-state patient households' real wage w_p , which results in the following steady-state value for patient households' labour supply l_p (equal to entrepreneurs' labour demand l_{pe} in equilibrium):

$$l_p = \left(\frac{\psi(1-\alpha)Y}{xc_p}\right)^{\frac{1}{1+\phi}} \tag{B.61}$$

 l_i (equivalently l_{ie}) is determined in a similar manner, using equations (B.56), (B.9) and (B15), as

$$l_i = \left(\frac{(1-\psi)(1-\alpha)Y}{xc_i}\right)^{\frac{1}{1+\phi}}$$
(B.62)

Next, I use l_p and l_i determined above along with equations (B.57) and (B.56), respectively, to derive the steady-state real wages to output ratios

$$\frac{w_p}{Y} = \frac{c_p l_p^{\phi}}{Y} \tag{B.63}$$

and

$$\frac{w_i}{Y} = \frac{c_i l_i^{\phi}}{Y} \tag{B.64}$$

Then, equation (B.5) allows me to deduct the steady-state value of the deposits to output ratio as

$$\frac{d_p}{Y} = \frac{(c_p - w_p l_p - J_R)}{r_d Y}$$
(B.65)

where the steady-state retail profits to output ratio $\frac{J_R}{Y} = 1 - \frac{1}{x}$ is obtained from equation (B.29), and the other expressions are given as above.

Finally, the steady-state rental price of capital is obtained using equations (B.20) and (B.50) as

$$r_k = \frac{\alpha}{x} \left(\frac{k_e}{Y}\right)^{-1} \tag{B.66}$$

B.3 A Credit Supply Shock Experiment

To illustrate the difference between the transmission channels of credit demand and supply shocks, I now provide in FIGURE B.1 below simulation results of a loan supply shock in the form of a sudden destruction of bank capital that can be interpreted as a weakening of banks balance-sheets.

For that, I follow Gerali et al. (2010) and write the law of motion for aggregate bank capital as

$$\pi_t K_{B,t} = \frac{(1-\delta_b)K_{B,t-1}}{\varepsilon_{K_B,t}} + J_{B,t-1}$$

where $log(\varepsilon_{K_B,t}) = (1 - \rho_{\varepsilon_{K_B}})log(\overline{\varepsilon}_{K_B}) + \rho_{\varepsilon_{K_B}}log(\varepsilon_{K_B,t-1}) + \epsilon_{K_B,t}$

is the exogenous shock to bank capital that weakens the banks' balance-sheets, with $\epsilon_{K_B,t} \sim$ i.i.d $N(0, \sigma_{\epsilon_{K_B}}^2)$.



FIGURE B.1: Effects of a Credit Supply Shock

Note: This figure reports the responses of financial and macroeconomic variables to an negative loan supply shock. Credit supply shocks mostly propagate to the economy through the Financial accelerator mechanism.

As one can see from FIGURE B.1 above, an adverse shock to bank capital leads to banks tightening access of loans to households and firms, through both a contraction in loans volume and an increase in lending rates. This will then lead to a decrease in consumption and investment, thus resulting in lower production. This, together with the reduced supply of funds by banks, will in turn lead to lower cash-flows that will depress asset prices, thus reducing the value of the collateral (houses and capital) that impatient households and firms can pledge for new loans in the subsequent period. This lower collateral value coupled with the weak bank balance-sheets, will next lead to further tightening of credit by banks, reducing investment, consumption, and production even further through the financial accelerator mechanism, and so on.



FIGURE B.2: Partial Equilibrium Illustration of Credit Supply Shocks

Note: This figure is a simple illustration of how exogenous loan supply shocks move credit quantity and price in opposite directions, all things else being equal. In this particular example, the initial equilibrium is at the kink point A_0 where the borrowing constraint binds.

Finally, FIGURE B.2 above illustrates how exogenous loan supply shocks move credit quantity and price in opposite directions, ceteris paribus. In this particular example, the initial equilibrium is at the kink point A_0 where borrowing constraints bind, so that a positive credit supply shock shifts CS_0 downwards resulting in a lower interest rate and no change in quantity $(B_2 = B_0)$ since the borrower is already at its debt limit. Intuitively, this loosening of access to loans by lenders has led to cheaper credit so that borrowers can still borrow at full capacity at a lower price R_2 . The opposite movement of loan quantity and price would indeed be more explicit if borrowers were below their debt limit before the shock hits. In the particular example at hand, this opposite movement of credit quantity and price is obvious in the event of a negative loan supply shock, as illustrated by the new equilibrium A_1 on the figure.

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